Which Anime Next? Recommendation System based on Content-based Filtering and Collaborative Filtering: Which Wins?

In [2]:
```
# import packages
import numpy as np
import pandas as pd
from pandas import Series
import seaborn as sns
import itertools
import os
import seaborn as sns
import re
import matplotlib.pyplot as plt

from collections import Counter
from wordcloud import WordCloud, STOPWORDS
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.metrics.pairwise import linear_kernel

from sklearn.preprocessing import MinMaxScaler


from sklearn.neighbors import NearestNeighbors
from sklearn.model_selection import train_test_split

from sklearn.preprocessing import OneHotEncoder
from sklearn.preprocessing import StandardScaler
from sklearn.impute import SimpleImputer
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import cross_val_predict
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score,
from sklearn.preprocessing import MinMaxScaler

from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.linear_model import SGDClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import LinearSVC
from sklearn.model_selection import GridSearchCV
```

In [3]:
```
# import data: need to change path if used on another PC
df_anime = pd.read_csv("F:\\UCL\\Term2\\projects\\new\\data\\anime.csv")
df_anime_with_synopsis = pd.read_csv("F:\\UCL\\Term2\\projects\\new\\data\\anime_with_
df_animelist = pd.read_csv("F:\\UCL\\Term2\\projects\\new\\data\\animelist.csv")
df_watching_status = pd.read_csv("F:\\UCL\\Term2\\projects\\new\\data\\watching_statu
```

In [4]:
```
# setting to show all columns of dataframes
pd.set_option("display.max_columns",None)
```

1. Data Preparation

In [5]:
```
# head of main dataset: df_anime
```

```
df_anime.head()
```

Out[5]:

	MAL_ID	Name	Score	Genders	English name	Japanese name	Type	Episodes	Aired	Premiered
0	1	Cowboy Bebop	8.78	Action, Adventure, Comedy, Drama, Sci-Fi, Space	Cowboy Bebop	カウボーイビバップ	TV	26	Apr 3, 1998 to Apr 24, 1999	Spring 1998
1	5	Cowboy Bebop: Tengoku no Tobira	8.39	Action, Drama, Mystery, Sci-Fi, Space	Cowboy Bebop:The Movie	カウボーイビバップ 天国の扉	Movie	1	Sep 1, 2001	Unknown
2	6	Trigun	8.24	Action, Sci-Fi, Adventure, Comedy, Drama, Shounen	Trigun	トライガン	TV	26	Apr 1, 1998 to Sep 30, 1998	Spring 1998
3	7	Witch Hunter Robin	7.27	Action, Mystery, Police, Supernatural, Drama, ...	Witch Hunter Robin	Witch Hunter ROBIN (ウイッチハンターロビン)	TV	26	Jul 2, 2002 to Dec 24, 2002	Summer 2002
4	8	Bouken Ou Beet	6.98	Adventure, Fantasy, Shounen, Supernatural	Beet the Vandel Buster	冒険王ビィト	TV	52	Sep 30, 2004 to Sep 29, 2005	Fall 2004

In [6]:

```
# show head of df_animelist
df_animelist.head()
```

Out[6]:

	user_id	anime_id	rating	watching_status	watched_episodes
0	0	67	9	1	1
1	0	6702	7	1	4
2	0	242	10	1	4
3	0	4898	0	1	1
4	0	21	10	1	0

In [7]:

```
# show head of anime synopsis
df_anime_with_synopsis.head()
```

Out[7]:

	MAL_ID	Name	Score	Genders	sypnopsis

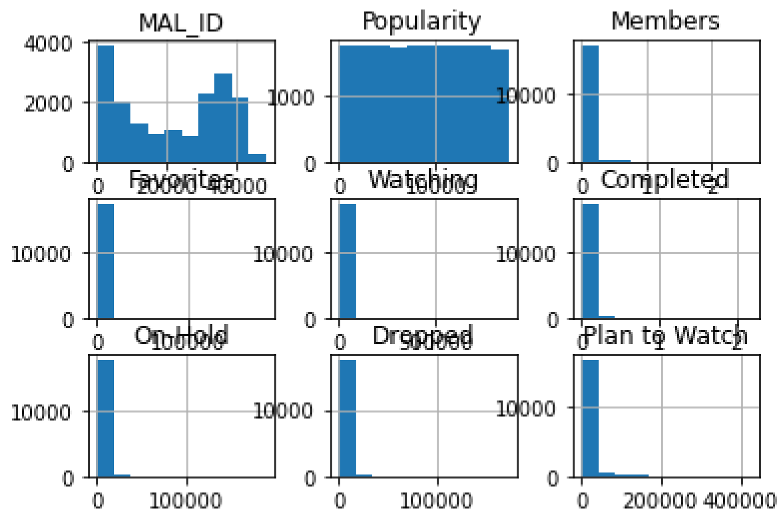
	MAL_ID	Name	Score	Genders	synopsis
0	1	Cowboy Bebop	8.78	Action, Adventure, Comedy, Drama, Sci-Fi, Space	In the year 2071, humanity has colonized sever...
1	5	Cowboy Bebop: Tengoku no Tobira	8.39	Action, Drama, Mystery, Sci-Fi, Space	other day, another bounty—such is the life of ...
2	6	Trigun	8.24	Action, Sci-Fi, Adventure, Comedy, Drama, Shounen	Vash the Stampede is the man with a $$60,000,0...
3	7	Witch Hunter Robin	7.27	Action, Mystery, Police, Supernatural, Drama, ...	ches are individuals with special powers like ...
4	8	Bouken Ou Beet	6.98	Adventure, Fantasy, Shounen, Supernatural	It is the dark century and the people are suff...

In [8]:

```
# check history of numerical variables
df_anime.hist()
```

Out[8]:

```
array([[<AxesSubplot:title={'center':'MAL_ID'}>,
        <AxesSubplot:title={'center':'Popularity'}>,
        <AxesSubplot:title={'center':'Members'}>],
       [<AxesSubplot:title={'center':'Favorites'}>,
        <AxesSubplot:title={'center':'Watching'}>,
        <AxesSubplot:title={'center':'Completed'}>],
       [<AxesSubplot:title={'center':'On-Hold'}>,
        <AxesSubplot:title={'center':'Dropped'}>,
        <AxesSubplot:title={'center':'Plan to Watch'}>]], dtype=object)
```



1.1 Deal with Unknowns

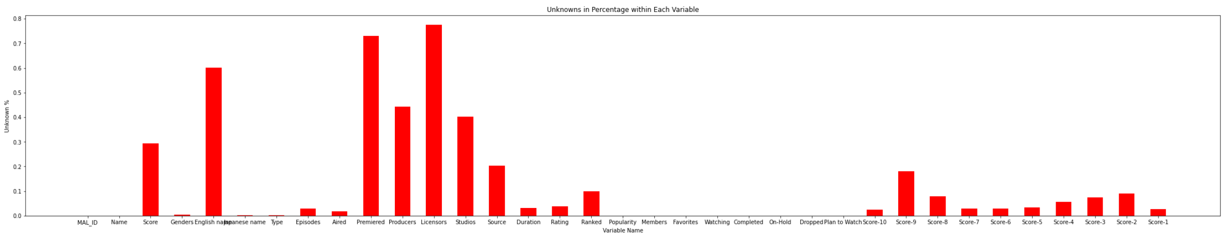
In [9]:

```
# count unknown variables
col_list=df_anime.columns
col_unknown_count_list=[]
for col in col_list:
    unknown_count=df_anime.loc[df_anime[col]=="Unknown",col].count()
    col_unknown_count_list.append(unknown_count/17562)

fig = plt.figure(figsize=(30,5))
ax = fig.add_axes([0,0,1,1])
ax.bar(col_list,col_unknown_count_list,color="red",width=[0.5])

ax.set_xlabel('Variable Name')
ax.set_ylabel('Unknown %')
ax.set_title("Unknowns in Percentage within Each Variable")
```

```
plt.show()
```



1.1.1 Scores

In [10]:
```
# get sum and count for a numerical column, to facilitate avg calculation
def get_sum(col_name):
    sum_score = 0
    count_score = 0
    for each_value in df_anime[col_name]:
        #print(each_value)
        if each_value != 'Unknown':
            sum_score+=int(float(each_value))
        else:
            count_score+=1
    return sum_score,count_score
```

In [11]:
```
# test funciton
get_sum('Score-10')
```

Out[11]: (43603379, 437)

In [12]:
```
# fill in with avg score for each score vriable
df_anime['Score-10'] = np.where((df_anime['Score-10']=='Unknown'), get_sum('Score-10'
df_anime['Score-9'] = np.where((df_anime['Score-9']=='Unknown'), get_sum('Score-9')[0
df_anime['Score-8'] = np.where((df_anime['Score-8']=='Unknown'), get_sum('Score-8')[0
df_anime['Score-7'] = np.where((df_anime['Score-7']=='Unknown'), get_sum('Score-7')[0
df_anime['Score-6'] = np.where((df_anime['Score-6']=='Unknown'), get_sum('Score-6')[0
df_anime['Score-5'] = np.where((df_anime['Score-5']=='Unknown'), get_sum('Score-5')[0
df_anime['Score-4'] = np.where((df_anime['Score-4']=='Unknown'), get_sum('Score-4')[0
df_anime['Score-3'] = np.where((df_anime['Score-3']=='Unknown'), get_sum('Score-3')[0
df_anime['Score-2'] = np.where((df_anime['Score-2']=='Unknown'), get_sum('Score-2')[0
df_anime['Score-1'] = np.where((df_anime['Score-1']=='Unknown'), get_sum('Score-1')[0
```

In [13]:
```
# change score type to float
df_anime[['Score-10', 'Score-9','Score-8','Score-7','Score-6','Score-5','Score-4','Sco
    'Score-10', 'Score-9','Score-8','Score-7','Score-6','Score-5','Score-4','Score-3',
```

1.1.2 Type

In [14]:
```
# just use TV for all unknowns because it is the most frequent category
df_anime["Type"].value_counts()
df_anime["Type"]= np.where((df_anime['Type']=='Unknown'), "TV", df_anime['Type'])
```

1.1.3 Rating

In [15]:
```
# use G - All Ages for all unknowns
df_anime["Rating"].value_counts()
df_anime["Rating"]=np.where((df_anime['Rating']=='Unknown'), "G - All Ages", df_anime
```

1.1.4 Episodes

In [16]:
```
# unknowns in episodes represent anime which is still on-going, most likely
print("number of unknown episodes anime:",df_anime[df_anime['Episodes']=='Unknown'].c

# calculate avg episodes for types of anime
sub_data=df_anime[["Episodes","Type"]].copy()
sub_data = sub_data.loc[sub_data['Episodes'] != 'Unknown']
sub_data["Episodes"] = pd.to_numeric(sub_data["Episodes"])
sub_data.groupby(['Type']).mean()
```

```
number of unknown episodes anime: 516
```

Out[16]:

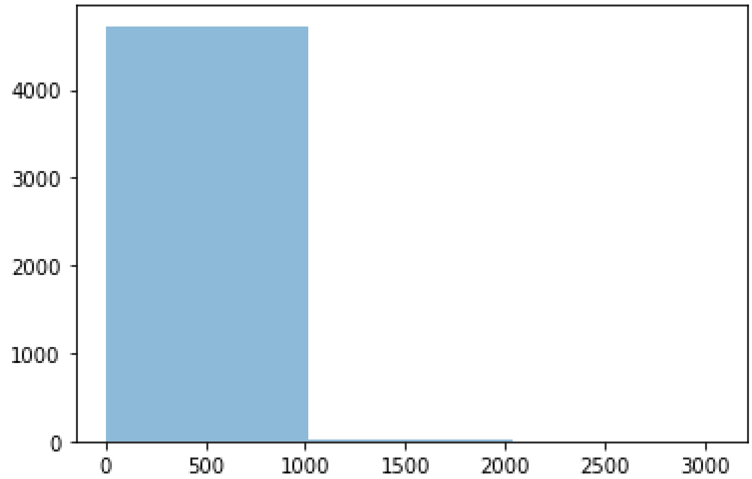
	Episodes
Type	
Movie	1.121132
Music	1.178718
ONA	8.916147
OVA	2.354973
Special	2.486758
TV	34.011402

In [17]:
```
# length of a movie is 1 episodes, makes sense, we will assign unknown episodes if the
# first assign movie and music to episode 1
df_anime['Episodes'] = np.where((df_anime['Type']=='Movie')
                                & (df_anime["Episodes"]=='Unknown'), 1, df_anim
df_anime['Episodes'] = np.where((df_anime['Type']=='Music')
                                & (df_anime["Episodes"]=='Unknown'), 1, df_anim
# ONA,OVA should be assined their avg
df_anime['Episodes'] = np.where((df_anime['Type']=='ONA')
                                & (df_anime["Episodes"]=='Unknown'), 9, df_anim
df_anime['Episodes'] = np.where((df_anime['Type']=='OVA')
                                & (df_anime["Episodes"]=='Unknown'), 3, df_anim
# special should be assign avg
df_anime['Episodes'] = np.where((df_anime['Type']=='Special')
                                & (df_anime["Episodes"]=='Unknown'), 2, df_anim
```

In [18]:
```
# abit different in TV, since the distribution of TV is wide

# frequency distribution of TV episodes
sub_data_type = sub_data.loc[(sub_data['Episodes'] != 'Unknown') & (sub_data["Type"]=
(n, bins, patches)= plt.hist(sub_data_type["Episodes"], bins=3,alpha=0.5)
plt.show()
print("number of unknown episodes anime which are Tv type:",len(sub_data_type["Episode
print(n,bins,patches)

# decide to use 800 as a break-up number and assign 800 to unknown episodes whose anim
df_anime['Episodes'] = np.where((df_anime['Type']=='TV')
                                & (df_anime["Episodes"]=='Unknown'), 800, df_an
```




```
number of unknown episodes anime which are Tv type: 4736
[4.728e+03 7.000e+00 1.000e+00] [1.00000000e+00 1.01966667e+03 2.03833333e+03 3.057000
00e+03] <BarContainer object of 3 artists>
```

1.1.5 Ranked

In [19]:

```
# calculate avg rank
sub_data_rank = df_anime["Ranked"].copy()
sub_data_rank = sub_data_rank.loc[sub_data_rank != 'Unknown']
print(sub_data_rank)
sub_data_rank = pd.to_numeric(sub_data_rank)
rank_mean=sub_data_rank.mean()

# fill in unknowns with avg
df_anime["Ranked"]=np.where((df_anime['Ranked']=='Unknown'), rank_mean, df_anime['Ran
```

```
0          28.0
1         159.0
2         266.0
3        2481.0
4        3710.0
          ...
17532    12882.0
17533    13980.0
17548        0.0
17552     5799.0
17556    12855.0
Name: Ranked, Length: 15800, dtype: object
```

1.1.6 Genders

In [20]:

```
# get rid of blank spaces
df_anime['Genders'] = df_anime['Genders'].str.replace(' ', '')
Genders_df=df_anime["Genders"].str.get_dummies(sep=",")
# print(Genders_df)

# the 5 most popular Genders
print(Genders_df.sum(axis=0).sort_values(ascending=False).head(5))

# add the 3 most popular genders to unknowns
df_anime["Genders"]=np.where((df_anime['Genders']=='Unknown'), "Comedy,Action,Fantasy
```

```
Comedy       6029
Action       3888
Fantasy      3285
Adventure    2957
Kids         2665
dtype: int64
```

1.1.7 Aired

In [21]:
```
# print number of anime with unknown aired variable
print("there are",df_anime.loc[df_anime["Aired"]=="Unknown"].count()[1],"unknowns for

# clean the aired to a specific year
df_anime['Aired'] = df_anime['Aired'].str.extract(r'(\d{4})')

# fill in unknowns with 2017, the most common year for aired
print(df_anime["Aired"].value_counts())
df_anime["Aired"]=np.where((df_anime['Aired']=='Unknown'), 2017, df_anime['Aired'])
```

```
there are 309 unknowns for aired
2017    922
2016    897
2018    882
2014    852
2015    792
       ...
1953      2
1955      2
1937      2
1944      1
1945      1
Name: Aired, Length: 101, dtype: int64
```

1.1.8 Score

In [22]:
```
# fill in with avg
sub_data_score = df_anime["Score"].copy()
sub_data_score = sub_data_score.loc[sub_data_score != 'Unknown']
print(sub_data_score)
sub_data_score = pd.to_numeric(sub_data_score)
score_mean=sub_data_score.mean()
df_anime["Score"]=np.where((df_anime['Score']=='Unknown'), score_mean, df_anime['Scor
```

```
0        8.78
1        8.39
2        8.24
3        7.27
4        6.98
         ...
17504    6.59
17505    7.52
17512    6.83
17513    4.81
17552    6.52
Name: Score, Length: 12421, dtype: object
```

1.1.8 Source

In [23]:
```
# show the category distribution of source
print(df_anime["Source"].value_counts())

# fill in with most common category: original
df_anime["Source"]=np.where((df_anime['Source']=='Unknown'), "Original", df_anime['So
```

```
Original        5215
Manga           3825
Unknown         3567
Visual novel     993
Game             880
Light novel      768
Other            597
Novel            510
Music            317
4-koma manga     288
Web manga        252
```

```
Picture book      147
Book              112
Card game          64
Digital manga      15
Radio              12
Name: Source, dtype: int64
```

1.1.9 Duration

In [24]:
```
#print(df_anime["Duration"][:50])
dur_dummy=df_anime["Duration"].str.split(" ")

# transfer the str and int combination string to integers in minutes to represent dura
clean_list=[]
for i in dur_dummy:
    #print(i)
    if i[0] !="Unknown":
        if len(i)==4:
            if (i[1]=="min.") & (i[0].isnumeric()) & (i[3]=="ep."):
                time_min=int(i[0])
            elif (i[0].isnumeric()) & (i[1]=="hr.") & (i[3]=="min."):
                time_min=int(i[0])*60+int(i[2])
        else:
            if (i[0].isnumeric()) & (i[1]=="sec."):
                time_min=1
            elif (i[1]=="min.") & (i[0].isnumeric()):
                time_min=int(i[0])
    else:
        time_min="Unknown"
    clean_list.append(time_min)
```

In [25]:
```
clean_list.count("Unknown")
# assigned the transferred value to the "duration"
df_anime["Duration"]=clean_list
```

In [26]:
```
# select data containing only known values to see the trends
sub_data_dur=df_anime[["Duration","Type"]].copy()
sub_data_dur = sub_data_dur.loc[sub_data_dur['Duration'] != 'Unknown']
sub_data_dur["Duration"] = pd.to_numeric(sub_data_dur["Duration"])
sub_data_dur.groupby(['Type']).mean()
```

Out[26]:

Type	Duration
Movie	51.966724
Music	3.348392
ONA	8.255556
OVA	28.109759
Special	18.726115
TV	19.646016

In [27]:
```
# assign unknowns with the mean of the type

df_anime['Duration'] = np.where((df_anime['Type']=='Movie')
                                & (df_anime["Duration"]=='Unknown'), 52, df_ani
df_anime['Duration'] = np.where((df_anime['Type']=='Music')
                                & (df_anime["Duration"]=='Unknown'), 3, df_anim
# ONA,OVA should be assined their avg
```

```
df_anime['Duration'] = np.where((df_anime['Type']=='ONA')
                                  & (df_anime["Duration"]=='Unknown'), 8, df_anim
df_anime['Duration'] = np.where((df_anime['Type']=='OVA')
                                  & (df_anime["Duration"]=='Unknown'), 28, df_ani
# special should be assign avg
df_anime['Duration'] = np.where((df_anime['Type']=='Special')
                                  & (df_anime["Duration"]=='Unknown'), 19, df_ani
# TV should be assign avg
df_anime['Duration'] = np.where((df_anime['Type']=='TV')
                                  & (df_anime["Duration"]=='Unknown'), 20, df_ani
```

1.1.10 Drop columns

In [28]:

```
# drop english name and japanses name since in name we have them all
df_anime_final = df_anime.drop(["English name","Japanese name"], 1)
```

1.2. Double check for missing values

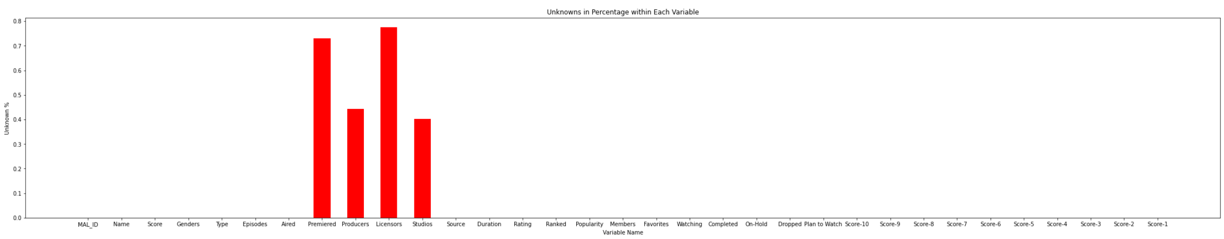
In [29]:

```
# again, count unknown
# for these 4 columns: Premiered,Producers,Licensors,Studios we still have unknowns
# but decide to keep them now since we have to use them in exploratory analysis and th
col_list=df_anime_final.columns
col_unknown_count_list=[]
for col in col_list:
    unknown_count=df_anime_final.loc[df_anime_final[col]=="Unknown",col].count()
    col_unknown_count_list.append(unknown_count/17562)

fig = plt.figure(figsize=(30,5))
ax = fig.add_axes([0,0,1,1])
ax.bar(col_list,col_unknown_count_list,color="red",width=[0.5])

ax.set_xlabel('Variable Name')
ax.set_ylabel('Unknown %')
ax.set_title("Unknowns in Percentage within Each Variable")

plt.show()
```



In [30]:

```
# other manipulations: change type of score to numeric
df_anime_final["Score"] = pd.to_numeric(df_anime_final["Score"])
```

2. Data Exploration

This section will represent some interesting graphs/trends for this dataset.

2.1 Anime Analysis

In [31]:

```
# categorical plot function
def category_plot(cate_name,plot_title,figsize=(7,4),width=0.7):
    category_names=df_anime_final[cate_name].value_counts().index.tolist()
    count_list=[]
    for name in category_names:
```

```
        count_each_name=df_anime_final.loc[df_anime_final[cate_name]==name,cate_name]
        count_list.append(count_each_name)
    fig = plt.figure(figsize=figsize)
    ax = fig.add_axes([0,0,1,1])
    ax.bar(category_names,count_list,width=width)

    ax.set_xlabel(cate_name)
    ax.set_ylabel("occurence count")
    ax.set_title(plot_title)
    plt.show()
```

2.1.1 Top 10 Anime

In [32]:

```
top10=df_anime_final[['Name', 'Score']].sort_values(by="Score",ascending=False).head
print(top10)
```

```
                                   Name  Score
3971       Fullmetal Alchemist: Brotherhood   9.19
15926  Shingeki no Kyojin: The Final Season   9.17
5683                            Steins;Gate   9.11
6474                     Hunter x Hunter (2011)   9.10
14963    Shingeki no Kyojin Season 3 Part 2   9.10
9913                               Gintama°    9.10
6006                               Gintama'   9.08
741                     Ginga Eiyuu Densetsu   9.07
7261                     Gintama': Enchousen   9.04
9886                         Koe no Katachi   9.00
```

2.1.2 Most Discussed Anime

In [33]:

```
top10_discussed=df_anime_final[['Name', 'Members']].sort_values(by="Members",ascendin
print(top10_discussed)
```

```
                               Name  Members
1393                     Death Note  2589552
7449             Shingeki no Kyojin  2531397
3971   Fullmetal Alchemist: Brotherhood  2248456
6614               Sword Art Online  2214395
10451                 One Punch Man  2123866
11185          Boku no Hero Academia  1909814
8646                    Tokyo Ghoul  1895488
10                           Naruto  1830540
5683                    Steins;Gate  1771162
8148                No Game No Life  1751054
```

2.1.2 Most watched anime: completed watching

In [34]:

```
top10_comp=df_anime_final[['Name', 'Completed']].sort_values(by="Completed",ascending
print(top10_comp)
```

```
                               Name  Completed
7449             Shingeki no Kyojin    2182587
1393                     Death Note    2146116
6614               Sword Art Online    1907261
10451                 One Punch Man    1841220
11185          Boku no Hero Academia    1655900
3971   Fullmetal Alchemist: Brotherhood    1644938
8646                    Tokyo Ghoul    1594880
10                           Naruto    1462223
11308                Kimi no Na wa.    1462143
8148                No Game No Life    1426896
```

2.1.2 Most favorated anime

In [35]:

```
top10_fav=df_anime_final[['Name', 'Favorites']].sort_values(by="Favorites",ascending=
```

```
print(top10_fav)
```

```
                                Name  Favorites
3971    Fullmetal Alchemist: Brotherhood     183914
5683                         Steins;Gate     148452
6474                  Hunter x Hunter (2011)     147274
1393                          Death Note     145201
7449                   Shingeki no Kyojin     129844
11                             One Piece     126645
1431    Code Geass: Hangyaku no Lelouch      90487
1574                   Naruto: Shippuuden      84651
20                 Neon Genesis Evangelion      71308
11308                      Kimi no Na wa.      71054
```

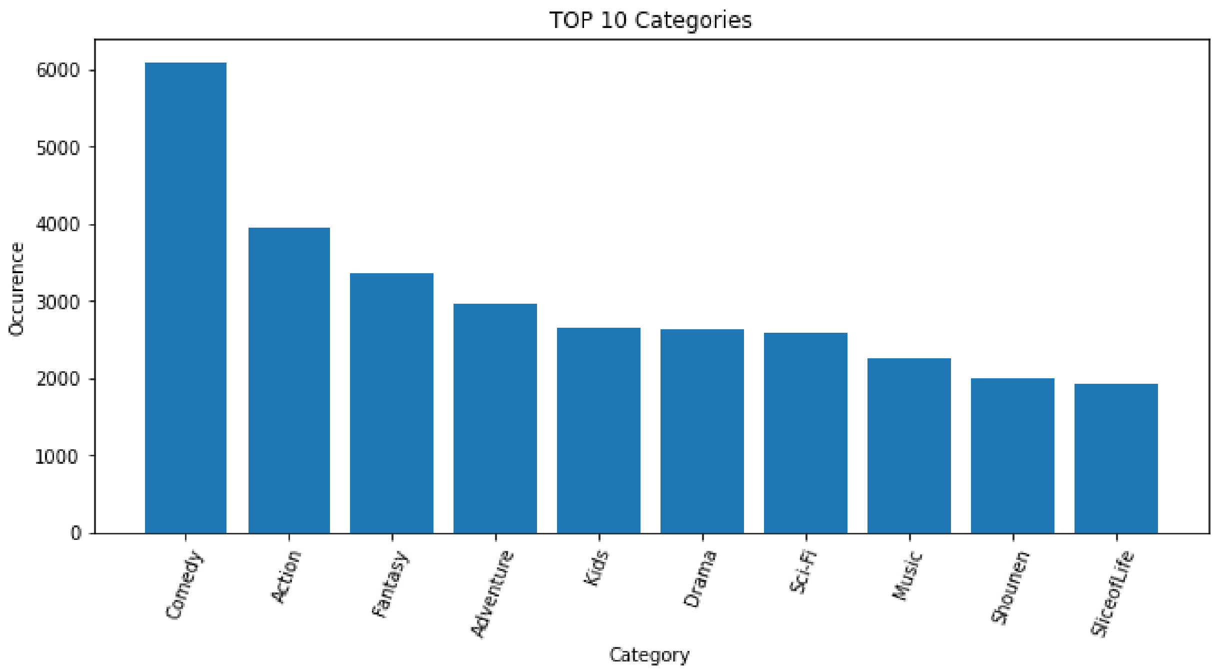
2.1.2 Top Anime Categories

In [36]:
```
genders_s=df_anime_final["Genders"].str.get_dummies(sep=",")
genders_s=genders_s.sum(axis=0).sort_values(ascending=False)
genders_df=pd.DataFrame({'Category':genders_s.index, 'Occurence':genders_s.values})
genders_df=genders_df.sort_values(by="Occurence",ascending=False)


top10_genders=genders_df[['Category', 'Occurence']].head(10)
data = top10_genders["Occurence"]
labels = top10_genders["Category"]
plt.figure(figsize=(11,5))
plt.xticks(range(len(data)), labels)
plt.xlabel('Category')

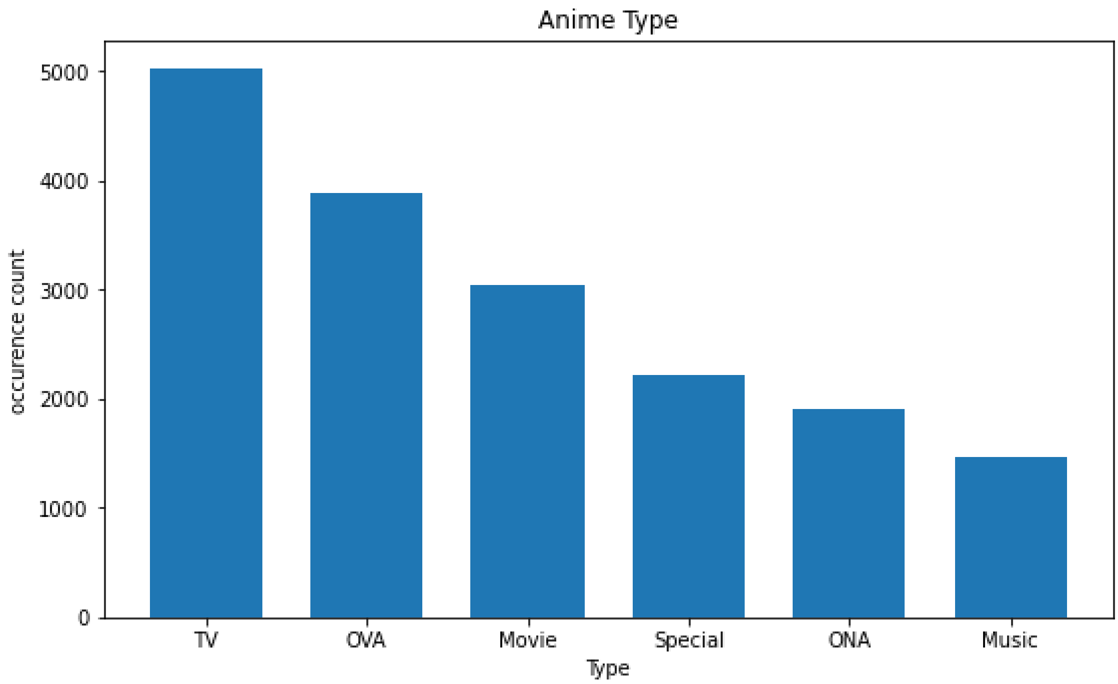
plt.ylabel('Occurence')
plt.xticks(rotation=70)

plt.title('TOP 10 Categories')
plt.bar(range(len(data)), data)
plt.show()
```



2.1.3 Top Anime Type

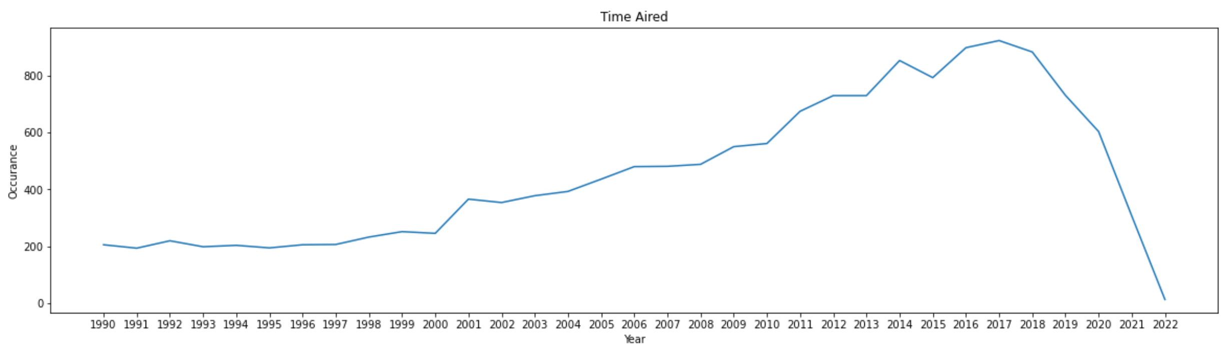
In [37]:
```
category_plot("Type","Anime Type")
```



2.1.4 Time of Aired

In [38]:
```
aired_s=df_anime_final["Aired"].value_counts()
aired_s=aired_s.sort_values()
aired_df=pd.DataFrame({'Year':aired_s.index, 'Occurance':aired_s.values})
# choose year after 1990
aired_df["Year"] = pd.to_numeric(aired_df["Year"])
aired_df=aired_df.loc[aired_df["Year"]>=1990]
aired_df=aired_df.sort_values(by="Year")
```

In [39]:
```
plt.figure(figsize=(20,5))
plt.plot(aired_df["Year"],aired_df["Occurance"])
plt.title('Time Aired')
plt.xlabel('Year')
plt.xticks(aired_df["Year"])
plt.ylabel('Occurance')
plt.show()
```



2.1.5 Top Producers/Licensors/Studios

Notice we have many unknowns for them, so the data is not completely categorizable; we only use the known values.

In [40]:
```
def cate_type2(col_name,title,occurance=False):
    producer_s=df_anime_final[col_name].value_counts()
    producer_s=producer_s.drop(labels=['Unknown'])
    producer_s=producer_s.sort_values()
    producer_df=pd.DataFrame({col_name:producer_s.index, 'Occurance':producer_s.value
```

```
    # choose year after 1990
    producer_df["Occurance"] = pd.to_numeric(producer_df["Occurance"])
    if occurance:
        producer_df=producer_df.loc[producer_df["Occurance"]>=occurance]

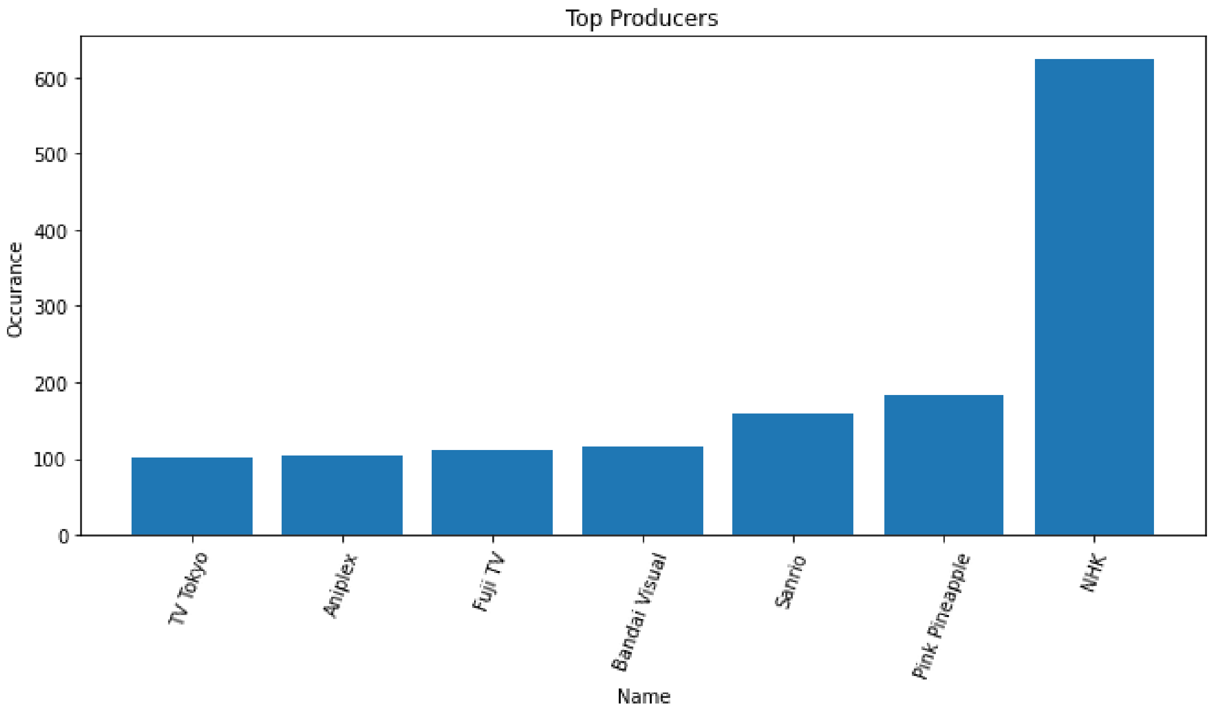
    data = producer_df["Occurance"]
    labels = producer_df[col_name]
    plt.figure(figsize=(11,5))
    plt.xticks(range(len(data)), labels)
    plt.xlabel('Name')

    plt.ylabel('Occurance')
    plt.xticks(rotation=70)

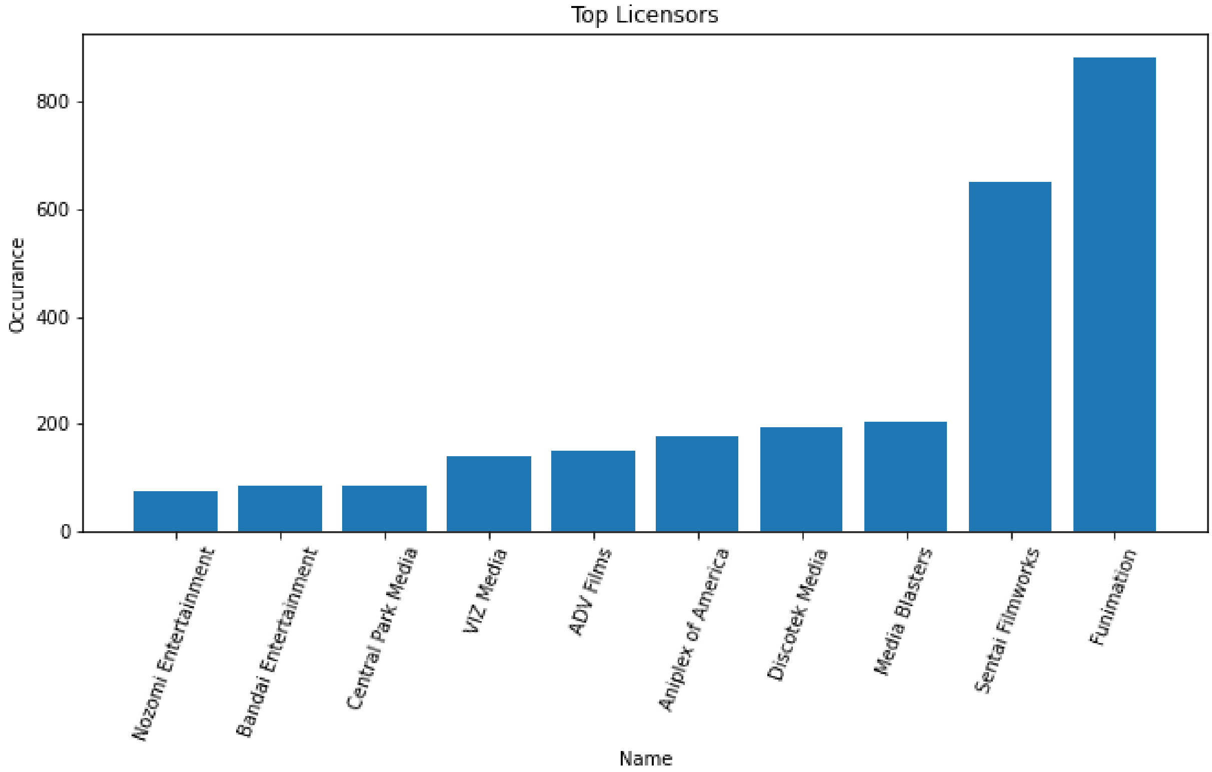
    plt.title(title)

    plt.bar(range(len(data)), data)
    plt.show()
```

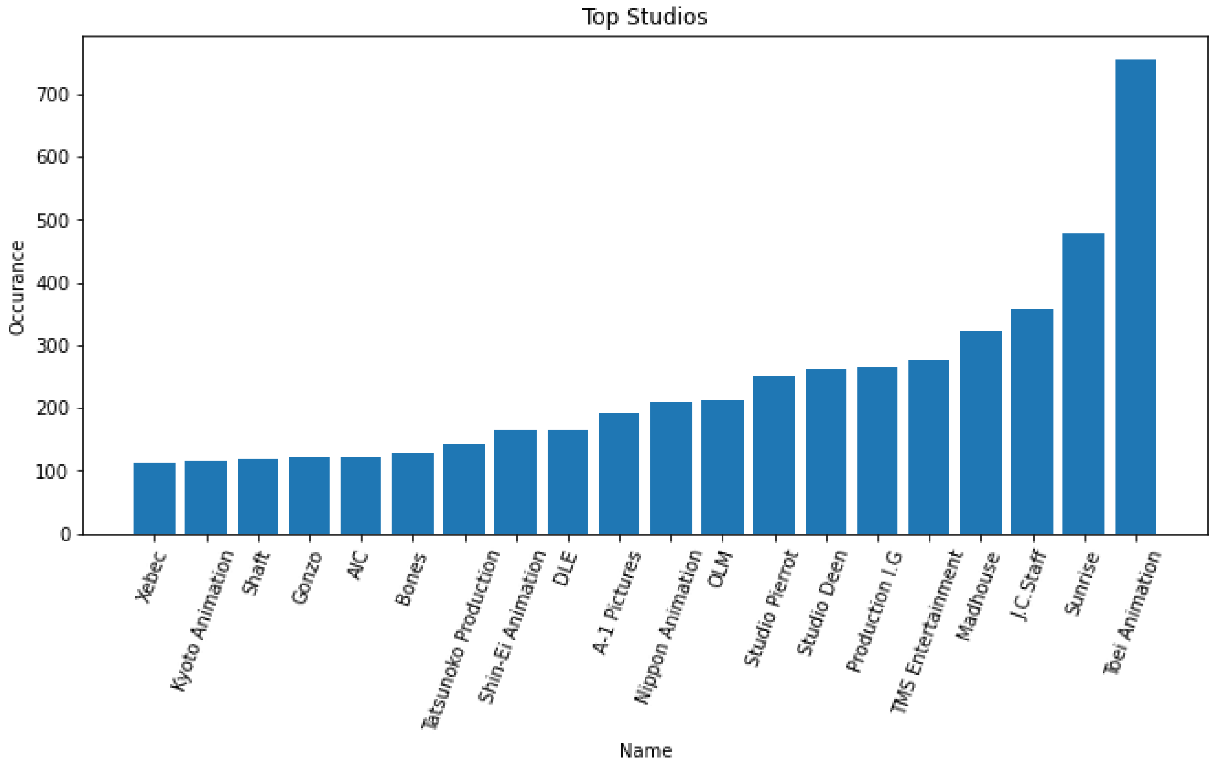
In [41]:
```
cate_type2("Producers","Top Producers",100)
```



In [42]:
```
cate_type2("Licensors","Top Licensors",70)
```



In [43]:
```
cate_type2("Studios","Top Studios",100)
```



2.1.5 Keywords in Anime

In [44]:
```
comment_words = ''
stopwords = set(STOPWORDS)

# iterate through the csv file
for val in df_anime_with_synopsis["sypnopsis"]:

    # typecaste each val to string
    val = str(val)
```

```
    # split the value
    tokens = val.split()

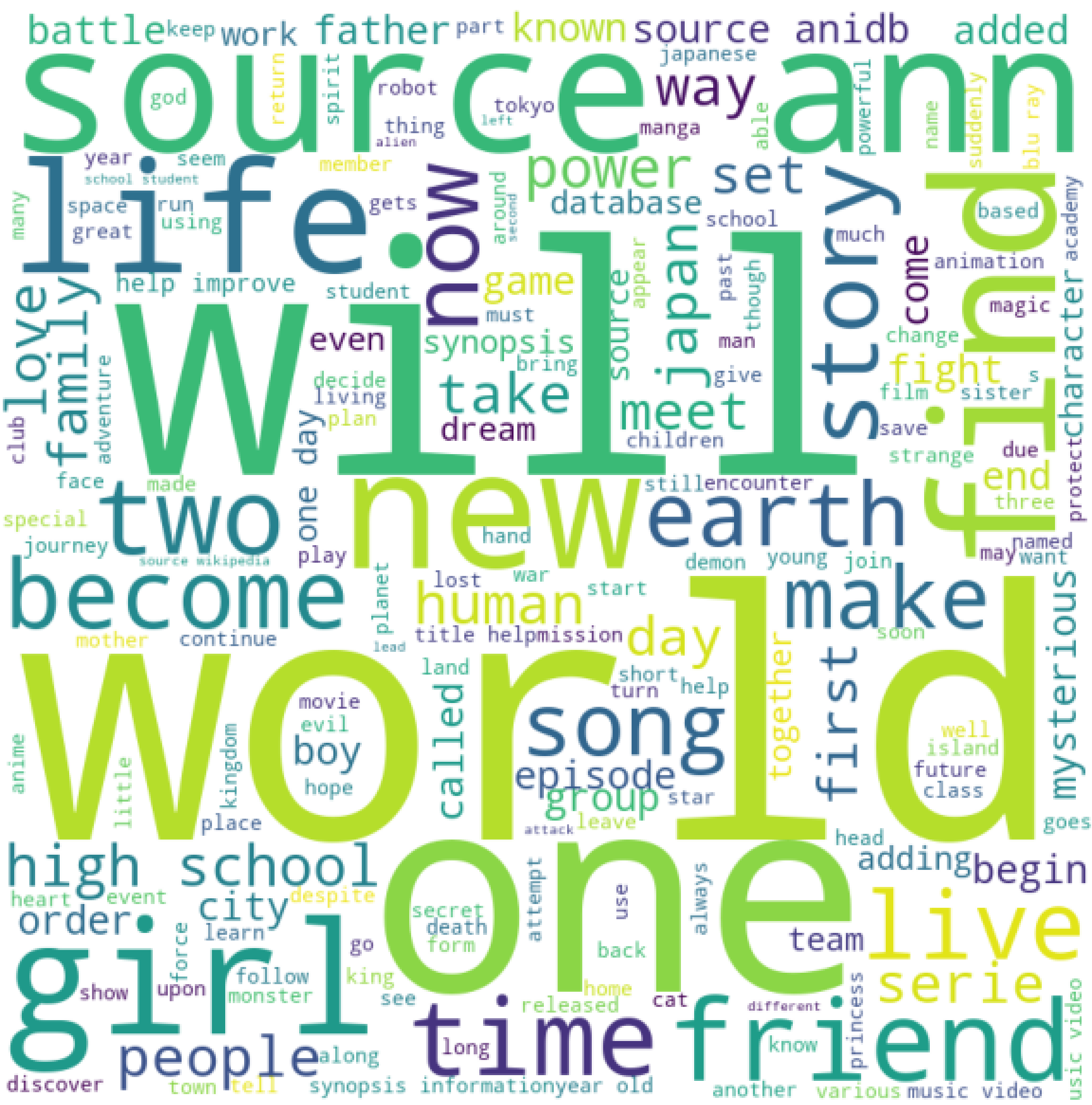
    # Converts each token into lowercase
    for i in range(len(tokens)):
        tokens[i] = tokens[i].lower()

    comment_words += " ".join(tokens)+" "

wordcloud = WordCloud(width = 800, height = 800,
                background_color ='white',
                stopwords = stopwords,
                min_font_size = 10).generate(comment_words)

# plot the WordCloud image
plt.figure(figsize = (8, 8), facecolor = None)
plt.imshow(wordcloud)
plt.axis("off")
plt.tight_layout(pad = 0)

plt.show()
```



2.2 User Analysis

2.2.1 User Watching Status

In [45]:
```
# rename variables
df_watching_status = df_watching_status.rename({'status': 'watching_status'}, axis=1)
```

In [46]:
```
# print
df_watching_status
```

Out[46]:

	watching_status	description
0	1	Currently Watching
1	2	Completed
2	3	On Hold
3	4	Dropped
4	6	Plan to Watch

In [47]:
```
# change variable type
df_animelist["user_id"] = pd.to_numeric(df_animelist["user_id"])
```

In [48]:
```
# decide to proceed with the first 100 users due to the large volumn of data
first_100_idx=df_animelist.loc[df_animelist["user_id"]==99].index[0]
df_merged_watching_filter=df_animelist[:first_100_idx+1]
```

In [49]:
```
# count each of the watching status for the first 100 user each
list_1=[]
list_2=[]
list_3=[]
list_4=[]
list_6=[]
for user in range(100):
    sub_df_user=df_merged_watching_filter.loc[df_merged_watching_filter['user_id']==u
    count1=sub_df_user.loc[sub_df_user["watching_status"]==1].count()[0]
    count2=sub_df_user.loc[sub_df_user["watching_status"]==2].count()[0]
    count3=sub_df_user.loc[sub_df_user["watching_status"]==3].count()[0]
    count4=sub_df_user.loc[sub_df_user["watching_status"]==4].count()[0]
    count6=sub_df_user.loc[sub_df_user["watching_status"]==6].count()[0]
    list_1.append(count1)
    list_2.append(count2)
    list_3.append(count3)
    list_4.append(count4)
    list_6.append(count6)
```

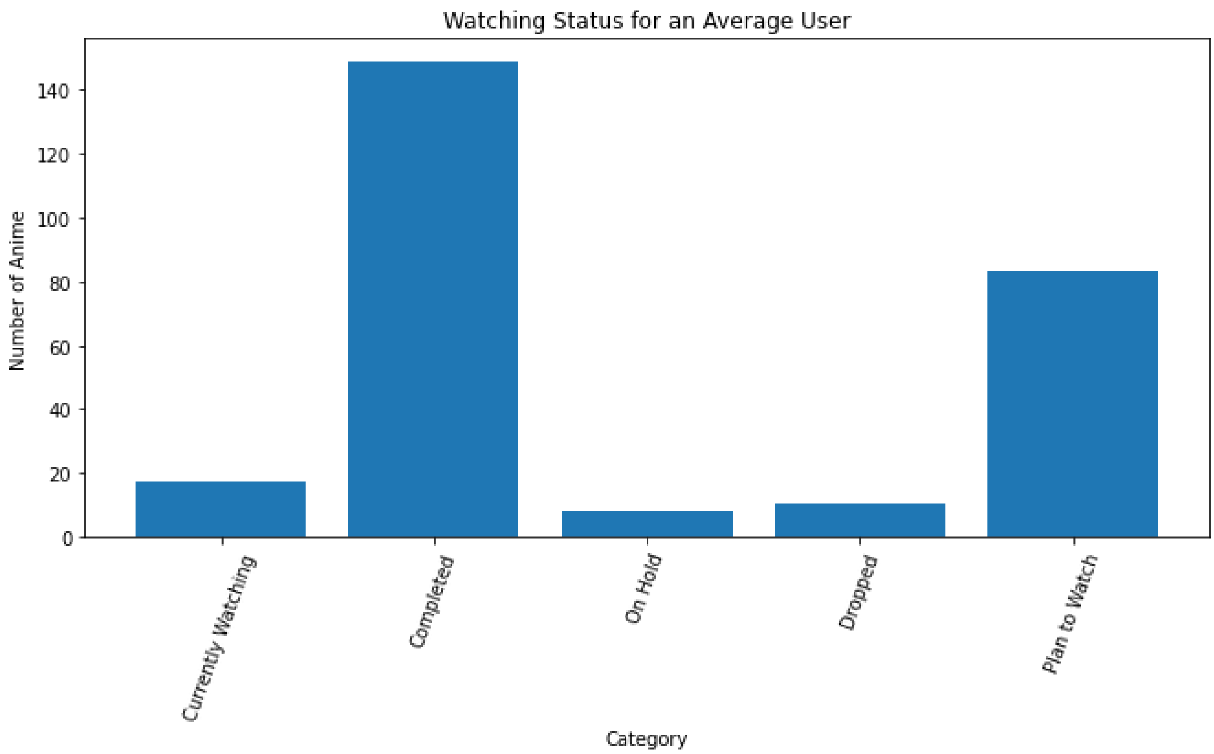
In [50]:
```
list1_avg=sum(list_1)/len(list_1)
list2_avg=sum(list_2)/len(list_2)
list3_avg=sum(list_3)/len(list_3)
list4_avg=sum(list_4)/len(list_4)
list6_avg=sum(list_6)/len(list_6)
lists_avg=[list1_avg,list2_avg,list3_avg,list4_avg,list6_avg]
lists_name=["Currently Watching","Completed","On Hold","Dropped","Plan to Watch"]
```

In [51]:
```
#plot bar
data = lists_avg
labels = lists_name
plt.figure(figsize=(11,5))
plt.xticks(range(len(data)), labels)
plt.xlabel('Category')

plt.ylabel('Number of Anime')
plt.xticks(rotation=70)

plt.title('Watching Status for an Average User')
```

```
plt.bar(range(len(data)), data)
plt.show()
```

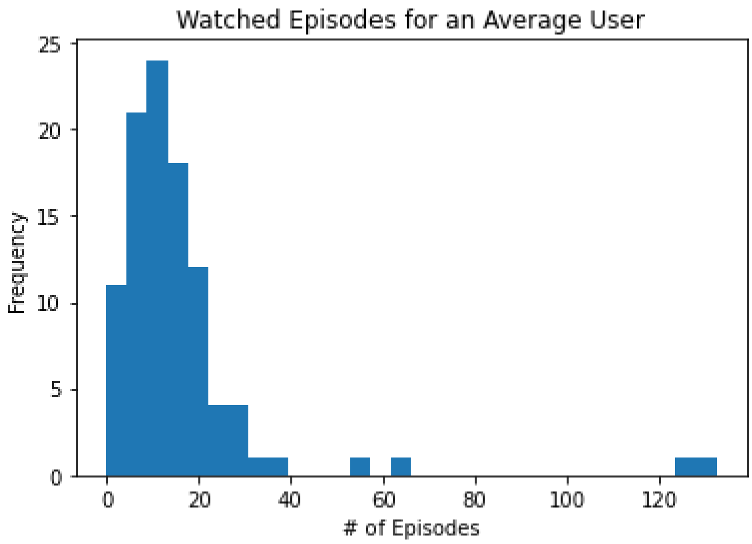


2.2.2 Episodes watched for each user/avg user

In [52]:
```
# histogram
list_eps=[]
for user in range(100):
    sub_df_user=df_merged_watching_filter.loc[df_merged_watching_filter['user_id']==u
    sum_ep=int(sub_df_user["watched_episodes"].sum())
    count_ep=int(sub_df_user["watched_episodes"].count())
    if count_ep==0:
        list_eps.append(0)
    else:
        list_eps.append(sum_ep/count_ep)
```

In [53]:
```
plt.hist(list_eps, density=False, bins=30)
plt.title("Watched Episodes for an Average User")
plt.ylabel('Frequency')
plt.xlabel('# of Episodes')
```

Out[53]: Text(0.5, 0, '# of Episodes')



2.3 Create New Feature --new score

In [54]:
```
# metrics to determine the top or popularity of anime
df_anime_final["new_score"] = (df_anime_final["Score-10"]*10+df_anime_final["Score-9"
                              +df_anime_final["Score-4"]*4+df_anime_final["Score-3"]*3+df_
```

In [55]:
```
#df_anime_final.head()
```

In [56]:
```
# now anime ranked with new score: weighted average
# rational: if a huge percent people give 10, then 10 should be weighted more
scored_anime = df_anime_final.sort_values('new_score', ascending=False)
scored_anime[['Name', 'new_score']].head(10)
```

Out[56]:

	Name	new_score
17226	Timeless Tree	9.998708
16914	The Third Eye	9.998477
17187	Han Hua Ri Ji 2nd Season	9.998277
17447	Drawing!!	9.997946
16025	Kabushikigaisha G-anime Saiyou Concept Movie	9.997356
17506	Kuiba Zhi Shu Tu	9.897355
17135	Spark Da!	9.848070
17146	Ton Ton Ton	9.848058
17436	Don't Cry (Movie)	9.848048
17167	Watashi no Nyanko	9.847990

3. Model Building

3.1 Content-based Filtering

Content-based filtering methods are based on a description of the item and a profile of the user's preferences. These methods are best suited to situations where there is known data on an item (name, location, description, etc.), but not on the user. Content-based recommenders treat recommendation as a user-specific classification problem and learn a classifier for the user's likes and dislikes based on an item's features.

In this system, keywords are used to describe the items and a user profile is built to indicate the type of item this user likes. In other words, these algorithms try to recommend items that are similar to those that a user liked in the past, or is examining in the present. It does not rely on a user sign-in mechanism to generate this often temporary profile. In particular, various candidate items are compared with items previously rated by the user and the best-matching items are recommended.

3.1.1 Vector Space Model (using synopsis)

In [57]:
```
# we are going to use keywords from name,genders,sypnopsis to indicate similarity
df_anime_with_synopsis.head()
```

Out[57]:

	MAL_ID	Name	Score	Genders	sypnopsis
0	1	Cowboy Bebop	8.78	Action, Adventure, Comedy, Drama, Sci-Fi, Space	In the year 2071, humanity has colonized sever...
1	5	Cowboy Bebop: Tengoku no Tobira	8.39	Action, Drama, Mystery, Sci-Fi, Space	other day, another bounty—such is the life of ...
2	6	Trigun	8.24	Action, Sci-Fi, Adventure, Comedy, Drama, Shounen	Vash the Stampede is the man with a $$60,000,0...
3	7	Witch Hunter Robin	7.27	Action, Mystery, Police, Supernatural, Drama, ...	ches are individuals with special powers like ...
4	8	Bouken Ou Beet	6.98	Adventure, Fantasy, Shounen, Supernatural	It is the dark century and the people are suff...

In [58]:
```
df_anime_with_synopsis.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 16214 entries, 0 to 16213
Data columns (total 5 columns):
 #   Column     Non-Null Count  Dtype 
---  ------     --------------  ----- 
 0   MAL_ID     16214 non-null  int64 
 1   Name       16214 non-null  object
 2   Score      16214 non-null  object
 3   Genders    16214 non-null  object
 4   sypnopsis  16206 non-null  object
dtypes: int64(1), object(4)
memory usage: 633.5+ KB
```

In [59]:
```
# Term Frequency-Inverse Document Frequency

# Define a TF-IDF Vectorizer Object. Remove all english stop words such as 'the', 'a'
tfidf = TfidfVectorizer(stop_words='english')

#Construct the required TF-IDF matrix by fitting and transforming the data
tfidf_matrix = tfidf.fit_transform(df_anime_with_synopsis['sypnopsis'].values.astype(

#Output the shape of tfidf_matrix: we have 45064 different vocabs, with total anime 16
tfidf_matrix.shape
```

Out[59]: (16214, 45064)

In [60]:
```
tfidf_matrix
```

Out[60]:
```
<16214x45064 sparse matrix of type '<class 'numpy.float64'>'
	with 488639 stored elements in Compressed Sparse Row format>
```

In [61]:
```
# check the vocabs
tfidf.get_feature_names()[1000:1010]
```

Out[61]:
```
['achilles',
 'aching',
 'achingly',
 'achived',
 'acid',
 'acidman',
 'ackdam',
 'acker',
 'ackerman',
 'acking']
```

In [62]:
```
# Compute the cosine similarity matrix
cosine_sim = linear_kernel(tfidf_matrix, tfidf_matrix)
```

In [63]:
```
cosine_sim
```

Out[63]:
```
array([[1.        , 0.23139075, 0.0159667 , ..., 0.        , 0.00988169,
        0.04593121],
       [0.23139075, 1.        , 0.03702934, ..., 0.        , 0.        ,
        0.01297045],
       [0.0159667 , 0.03702934, 1.        , ..., 0.        , 0.        ,
        0.        ],
       ...,
       [0.        , 0.        , 0.        , ..., 1.        , 0.        ,
        0.        ],
       [0.00988169, 0.        , 0.        , ..., 0.        , 1.        ,
        0.01655197],
       [0.04593121, 0.01297045, 0.        , ..., 0.        , 0.01655197,
        1.        ]])
```

In [64]:
```
cosine_sim.shape
```

Out[64]:
```
(16214, 16214)
```

In [65]:
```
cosine_sim[0]
```

Out[65]:
```
array([1.        , 0.23139075, 0.0159667 , ..., 0.        , 0.00988169,
       0.04593121])
```

In [66]:
```
#Construct a reverse map of indices and anime titles
indices = pd.Series(df_anime_with_synopsis.index, index=df_anime_with_synopsis['Name'
```

In [67]:
```
indices
```

Out[67]:
```
Name
Cowboy Bebop                        0
Cowboy Bebop: Tengoku no Tobira     1
Trigun                              2
Witch Hunter Robin                  3
Bouken Ou Beet                      4
                                 ...
Daomu Biji Zhi Qinling Shen Shu 16209
Mieruko-chan                    16210
Higurashi no Naku Koro ni Sotsu 16211
Yama no Susume: Next Summit     16212
Scarlet Nexus                   16213
Length: 16214, dtype: int64
```

In [68]:
```
# Function that takes in anime name as input and outputs most similar anime
def get_recommendations(name,num_to_rec,cosine_sim=cosine_sim):
    # Get the index of the name that matches the title
    idx = indices[name]

    # Get the pairwsie similarity scores of all anime with that anime
    sim_scores = list(enumerate(cosine_sim[idx]))
    # print(sim_scores)

    # Sort the anime based on the similarity scores
    sim_scores = sorted(sim_scores, key=lambda x: x[1], reverse=True)
    #print(sim_scores)

    # Get the scores of the n most similar anime
    sim_scores = sim_scores[1:num_to_rec+1]

    # Get the anime indices
    anime_indices = [i[0] for i in sim_scores]

    # Return the top 5 most similar anime
    return df_anime_with_synopsis['Name'].iloc[anime_indices]
```

In [69]:
```
# test
get_recommendations("Naruto",5) # name of anime, number of anime to recommend
```

Out[69]:
```
1508                                  Naruto: Shippuuden
11346                    Boruto: Naruto Next Generations
6158               Naruto: Shippuuden Movie 6 - Road to Ninja
3103       Naruto: Shippuuden - Shippuu! "Konoha Gakuen" Den
8831                             Boruto: Naruto the Movie
Name: Name, dtype: object
```

3.1.1.1 Setting for Evaluation

In [70]:
```
# prepare dataset for evaluation
df_animelist.head()
df_anime_with_synopsis = df_anime_with_synopsis.rename({'MAL_ID': 'anime_id'}, axis=1
df_anime_final = df_anime_final.rename({'MAL_ID': 'anime_id'}, axis=1)
```

In [71]:
```
df_all_anime=df_anime_with_synopsis[[ "anime_id","Name"]]
```

In [72]:
```
# decide to proceed with the first 500 users due to the large volumn of data
fist_500_idx=df_animelist.loc[df_animelist["user_id"]==500].index[0]
df_animelist_fist500=df_animelist[:fist_500_idx-1]
```

In [73]:
```
df_user_anime=pd.merge(df_animelist_fist500,df_all_anime, on = 'anime_id')
df_user_anime=pd.merge(df_user_anime,df_anime_final, on ="anime_id")
```

In [74]:
```
df_user_anime=df_user_anime.sort_values(by="user_id").reset_index(drop=True)
df_user_anime.head()
```

Out[74]:

	user_id	anime_id	rating	watching_status	watched_episodes	Name_x	Name_y	Score	
0	0	67	9	1	1	Basilisk: Kouga Ninpou Chou	Basilisk: Kouga Ninpou Chou	7.58	Ac

	user_id	anime_id	rating	watching_status	watched_episodes	Name_x	Name_y	Score	
1	0	431	8	2	1	Howl no Ugoku Shiro	Howl no Ugoku Shiro	8.67	
2	0	2762	9	2	24	Igano Kabamaru	Igano Kabamaru	7.87	Actior
3	0	570	7	2	1	Jin-Rou	Jin-Rou	7.79	
4	0	3418	9	2	50	Jungle no Ouja Taa-chan	Jungle no Ouja Taa-chan	7.01	

In [75]:
```
df_user_anime = df_user_anime.rename({'Name_x': 'Name'}, axis=1)
```

In [76]:
```
df_user_anime = df_user_anime.drop(["Name_y"], 1)
```

In [77]:
```
df_user_anime_features=df_user_anime[["user_id","anime_id","Name","rating","watching_s
                                      "Episodes","Aired","Duration","Ranked","Popularity","Membe
                                      "Favorites","Watching","Completed","On-Hold","Dropped","Pl
```

In [78]:
```
anime_features_for_each_user=df_user_anime_features.copy()
                          # the rest do not include because encoded types shape do not
                                        #df_user_anime["Genders"].str.get_dummies(sep=
                          #pd.get_dummies(df_user_anime["Type"]),
                          #pd.get_dummies(df_user_anime["Source"])],axis=1)
```

In [79]:
```
# final combianed user data and anime data table
anime_features_for_each_user.head()
```

Out[79]:

	user_id	anime_id	Name	rating	watching_status	watched_episodes	Score	Episodes	Aired
0	0	67	Basilisk: Kouga Ninpou Chou	9	1	1	7.58	24	2005
1	0	431	Howl no Ugoku Shiro	8	2	1	8.67	1	2004
2	0	2762	Igano Kabamaru	9	2	24	7.87	24	1983
3	0	570	Jin-Rou	7	2	1	7.79	1	2000
4	0	3418	Jungle no Ouja Taa-chan	9	2	50	7.01	50	1993

In [80]:
```
def get_anime_for_user(user_id):
    new_df=df_user_anime.loc[df_user_anime["user_id"]==user_id]
    #print("user",user_id,"has watched",len(new_df["Name"]),"anime!")
    return new_df["Name"].tolist()

# get anime list for anime that a user doesnt like: criteria: dropped anime and anime
def get_dislike_anime(user_id):
    average_rating= 6
    dislike_df=df_user_anime.loc[(df_user_anime["user_id"]==user_id)]
    dislike_df=dislike_df.loc[(df_user_anime["watching_status"]==4) | (df_user_anime[

    return dislike_df["Name"].tolist()

# define functions to get the relevant anime for a user
def relevant_anime_for_user(user_id):
    anime_list = get_anime_for_user(user_id)
    #print(anime_list)
    dislike_list = get_dislike_anime(user_id)
    #print(dislike_list)
    relevant_list = [anime for anime in anime_list if anime not in dislike_list]
    return relevant_list
```

In [81]:
```
# start off by assigning 0 to column 'liked'
anime_features_for_each_user["Liked"]=0
```

In [82]:
```
# new column: mark 1 for all liked anime for each user
for i in range(500):
    for rel_anime in relevant_anime_for_user(i):
        #print(rel_anime)
        index_liked=df_user_anime[(df_user_anime["user_id"]==i) & (df_user_anime["Nam
        # print(index_liked)
        anime_features_for_each_user.loc[index_liked, 'Liked'] = 1
```

In [83]:
```
# see like and dislike split in the training dataset
anime_features_for_each_user["Liked"].value_counts()
```

Out[83]:
```
0    77763
1    70078
Name: Liked, dtype: int64
```

In [84]:
```
# get recommendation list for a user: for anime that deeemed relevant to a user, recom
def recommendation_list(user_id):
    list_to_walk_thr=relevant_anime_for_user(user_id)
    #print(list_to_walk_thr)
    rec_list =[]
    count=0
    for anime in list_to_walk_thr:
        try:
            alist=get_recommendations(anime,10).tolist()
            count+=1
        #print(count)
        #print(alist)
            rec_list.append(alist)
        # handle errors
        except:
            #print("failed")
            pass
    #print(count)
    #print(rec_list)
    flattened_list = [val for sublist in rec_list for val in sublist]
    # print(len(flattened_list),"anime has been recommended")
    # set removes duplicaed recommendations
    return set(flattened_list)
```

In [85]:
```
# test the outcome of the function
list(recommendation_list(1))[:10]
```

Out[85]:
```
['Hello Kitty no Yuki no Joou',
 'Hunter x Hunter: Greed Island',
 'Shippuu! Iron Leaguer',
 'Re:Petit kara Hajimeru Isekai Seikatsu',
 'No.6',
 'One Piece: Romance Dawn Story',
 'Kizumonogatari I: Tekketsu-hen',
 "Cat's Eye",
 'Yu☆Gi☆Oh! The Dark Side of Dimensions',
 'Mouse']
```

3.1.1.2 Model Selection: 3-fold cross validation

logistic regression

In [86]:
```
# porform cross validation on first 100 sample users
precision_containor_cv=[]
recall_containor_cv=[]
f1_containor_cv=[]
for i in range(100):
    target_df_user=anime_features_for_each_user.loc[anime_features_for_each_user["use
    # drop air since it has nan, drop rating, watching statues and episodes since thes
    target_df_user_final=target_df_user.drop(["rating","watching_status","watched_epi
    x_train=target_df_user_final[target_df_user_final.columns[3:-1]]
    y_train=target_df_user_final["Liked"]

    try:
        norm = MinMaxScaler().fit(x_train)
        # transform training data
        x_transformed = norm.transform(x_train)


        # logistic classifier
        clf_logistic=LogisticRegression(random_state=42,max_iter=8000) # increase the
        # logistic regression: 10-fold cv
        pred_log=cross_val_predict(clf_logistic,x_transformed,y_train,cv=3)
        pre_logistic=precision_score(y_train,pred_log)
        recall_logistic=recall_score(y_train,pred_log)
        f1_logistic=f1_score(y_train,pred_log)

        # add cv score to lists
        precision_containor_cv.append(pre_logistic)
        recall_containor_cv.append(recall_logistic)
        f1_containor_cv.append(f1_logistic)

    except Exception as e:
        #print(e)
        pass
```

```
D:\Anaconda\lib\site-packages\sklearn\metrics\_classification.py:1221: UndefinedMetric
Warning: Precision is ill-defined and being set to 0.0 due to no predicted samples. Us
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least populated class in y has only 2 members, which is less than n_splits=3.
  warnings.warn(("The least populated class in y has only %d"
```

In [12…

```
# get rid of 0
precision_containor_cv=[x for x in precision_containor_cv if x!=0]
recall_containor_cv=[x for x in recall_containor_cv if x!=0]
f1_containor_cv=[x for x in f1_containor_cv if x!=0]

precision_final_log=sum(precision_containor_cv)/len(precision_containor_cv)
recall_final_log=sum(recall_containor_cv)/len(recall_containor_cv)
f1_final_log=sum(f1_containor_cv)/len(f1_containor_cv)
print(precision_final_log,recall_final_log,f1_final_log)
```

```
0.6746876030323176 0.7090003715648148 0.6590388773104608
```

decision tree

In [12…

```
# porform cross validation on first 100 sample users
precision_containor_tree=[]
recall_containor_tree=[]
f1_containor_tree=[]
for i in range(100):
    target_df_user=anime_features_for_each_user.loc[anime_features_for_each_user["use
    # drop air since it has nan, drop rating, watching statues and episodes since thes
    target_df_user_final=target_df_user.drop(["rating","watching_status","watched_epi
    x_train=target_df_user_final[target_df_user_final.columns[3:-1]]
    y_train=target_df_user_final["Liked"]

    try:
        norm = MinMaxScaler().fit(x_train)
        # transform training data
        x_transformed = norm.transform(x_train)
```

```
        # logistic classifier
        clf_tree = DecisionTreeClassifier(random_state=42)
        # logistic regression: 10-fold cv
        pred_tree=cross_val_predict(clf_tree,x_transformed,y_train,cv=3)
        pre_tree=precision_score(y_train,pred_tree)
        recall_tree=recall_score(y_train,pred_tree)
        f1_tree=f1_score(y_train,pred_log)

        # add cv score to lists
        precision_containor_tree.append(pre_tree)
        recall_containor_tree.append(recall_tree)
        f1_containor_tree.append(f1_tree)

    except Exception as e:
        #print(e)
        pass
```

```
D:\Anaconda\lib\site-packages\sklearn\model_selection\_split.py:670: UserWarning: The least populated class in y has only 2 members, which is less than n_splits=3.
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  _warn_prf(average, modifier, msg_start, len(result))
```

In [12…

```
# get rid of 0
precision_containor_tree=[x for x in precision_containor_tree if x!=0]
recall_containor_tree=[x for x in recall_containor_tree if x!=0]
f1_containor_tree=[x for x in f1_containor_tree if x!=0]

precision_final_tree=sum(precision_containor_tree)/len(precision_containor_tree)
recall_final_tree=sum(recall_containor_tree)/len(recall_containor_tree)
```

```
f1_final_tree=sum(f1_containor_tree)/len(f1_containor_tree)
print(precision_final_tree,recall_final_tree,f1_final_tree)
```

```
0.6666666666666666 0.5833333333333334 0.5714285714285715
```

support vector machine

In [12…

```
# perform cross validation on first 100 sample users
precision_containor_svc=[]
recall_containor_svc=[]
f1_containor_svc=[]
for i in range(100):
    target_df_user=anime_features_for_each_user.loc[anime_features_for_each_user["use
    # drop air since it has nan, drop rating, watching statues and episodes since thes
    target_df_user_final=target_df_user.drop(["rating","watching_status","watched_epi
    x_train=target_df_user_final[target_df_user_final.columns[3:-1]]
    y_train=target_df_user_final["Liked"]

    try:
        norm = MinMaxScaler().fit(x_train)
        # transform training data
        x_transformed = norm.transform(x_train)


        # logistic classifier
        clf_svc = LinearSVC(random_state=42)
        # logistic regression: 10-fold cv
        pred_svc=cross_val_predict(clf_tree,x_transformed,y_train,cv=3)
        pre_svc=precision_score(y_train,pred_svc)
        recall_svc=recall_score(y_train,pred_svc)
        f1_svc=f1_score(y_train,pred_svc)

        # add cv score to lists
        precision_containor_svc.append(pre_svc)
        recall_containor_svc.append(recall_svc)
        f1_containor_svc.append(f1_svc)

    except Exception as e:
        #print(e)
        pass
```

```
D:\Anaconda\lib\site-packages\sklearn\model_selection\_split.py:670: UserWarning: The
least populated class in y has only 2 members, which is less than n_splits=3.
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  _warn_prf(average, modifier, msg_start, len(result))
D:\Anaconda\lib\site-packages\sklearn\metrics\_classification.py:1221: UndefinedMetric
```

```
Warning: Recall is ill-defined and being set to 0.0 due to no true samples. Use `zero_
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  _warn_prf(
```

In [12…

```
# get rid of 0
precision_containor_svc=[x for x in precision_containor_svc if x!=0]
recall_containor_svc=[x for x in recall_containor_svc if x!=0]
f1_containor_svc=[x for x in f1_containor_svc if x!=0]

precision_final_svc=sum(precision_containor_svc)/len(precision_containor_svc)
recall_final_svc=sum(recall_containor_svc)/len(recall_containor_svc)
f1_final_svc=sum(f1_containor_svc)/len(f1_containor_svc)
print(precision_final_svc,recall_final_svc,f1_final_svc)
```

```
0.6463001811424754 0.6424084929136081 0.6435913973264247
```

kneighborclassifier

In [12…

```
# perform cross validation on first 100 sample users
precision_containor_kn=[]
recall_containor_kn=[]
f1_containor_kn=[]
for i in range(100):
    target_df_user=anime_features_for_each_user.loc[anime_features_for_each_user["use
    # drop air since it has nan, drop rating, watching statues and episodes since thes
    target_df_user_final=target_df_user.drop(["rating","watching_status","watched_epi
    x_train=target_df_user_final[target_df_user_final.columns[3:-1]]
    y_train=target_df_user_final["Liked"]

    try:
        norm = MinMaxScaler().fit(x_train)
        # transform training data
        x_transformed = norm.transform(x_train)


        # logistic classifier
        clf_kn = KNeighborsClassifier()
        # logistic regression: 10-fold cv
        pred_kn=cross_val_predict(clf_kn,x_transformed,y_train,cv=3)
        pre_kn=precision_score(y_train,pred_kn)
        recall_kn=recall_score(y_train,pred_kn)
        f1_kn=f1_score(y_train,pred_kn)

        # add cv score to lists
        precision_containor_kn.append(pre_kn)
```

```
            recall_containor_kn.append(recall_kn)
            f1_containor_kn.append(f1_kn)

        except Exception as e:
            #print(e)
            pass
```

```
D:\Anaconda\lib\site-packages\sklearn\metrics\_classification.py:1221: UndefinedMetric
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```
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Warning: F-score is ill-defined and being set to 0.0 due to no true nor predicted samp
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  _warn_prf(
```

In [12…

```
# get rid of 0
precision_containor_kn=[x for x in precision_containor_kn if x!=0]
recall_containor_kn=[x for x in recall_containor_kn if x!=0]
f1_containor_kn=[x for x in f1_containor_kn if x!=0]

precision_final_kn=sum(precision_containor_kn)/len(precision_containor_kn)
recall_final_kn=sum(recall_containor_kn)/len(recall_containor_kn)
f1_final_kn=sum(f1_containor_kn)/len(f1_containor_kn)
print(precision_final_kn,recall_final_kn,f1_final_kn)
```

```
0.6503842242333043 0.67277878732066 0.6532520776188653
```

CV comparison

In [12…

```
# fix number of neighbours to 5
log_all=[precision_final_log,recall_final_log,f1_final_log]
tree_all=[precision_final_tree,recall_final_tree,f1_final_tree]
svc_all=[precision_final_svc,recall_final_svc,f1_final_svc]
kn_all=[precision_final_kn,recall_final_kn,f1_final_kn]


# plot figure
plt.figure(figsize=(10,6))

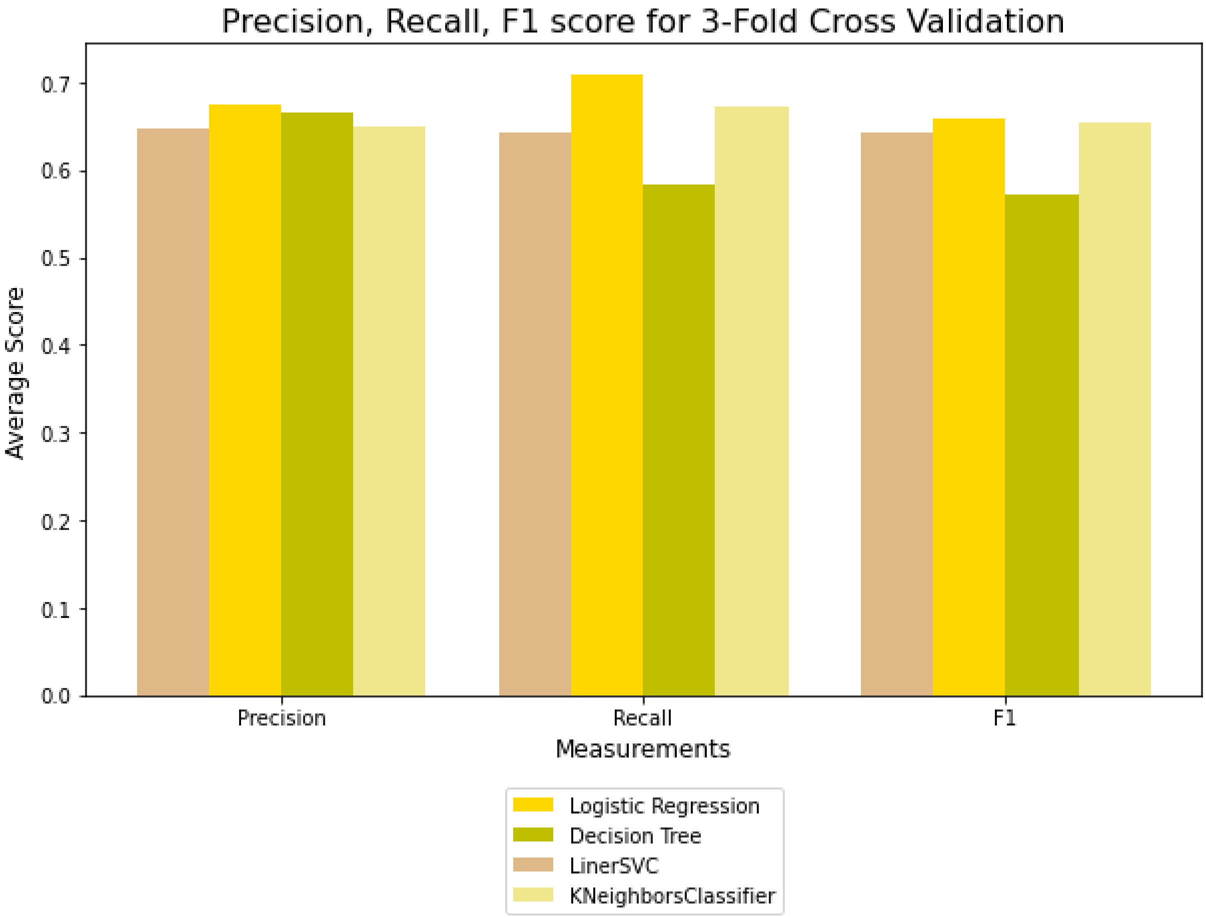
x_axis_name = ["Precision","Recall","F1"]

X_axis = np.arange(len(x_axis_name))

plt.bar(X_axis - 0.1, log_all, 0.2, label = 'Logistic Regression',color="gold")
plt.bar(X_axis + 0.1, tree_all, 0.2, label = 'Decision Tree',color="y")
plt.bar(X_axis - 0.3, svc_all, 0.2, label = 'LinerSVC',color="burlywood")
plt.bar(X_axis + 0.3, kn_all, 0.2, label = 'KNeighborsClassifier',color="khaki")

plt.xticks(X_axis, x_axis_name)
plt.xlabel("Measurements",fontsize=12)
plt.ylabel("Average Score",fontsize=12)
plt.title("Precision, Recall, F1 score for 3-Fold Cross Validation",fontsize=16)
plt.legend(loc="lower center", bbox_to_anchor=(0.5, -0.35))

fig.subplots_adjust(bottom=0.25)
plt.show()
```



3.1.1.3 MAP

In [87]:

```
precision_containor=[]
position_containor_cbv=[]
for i in range(100):
    target_df_user=anime_features_for_each_user.loc[anime_features_for_each_user["use
    # drop air since it has nan, drop rating, watching statues and episodes since thes
    target_df_user_final=target_df_user.drop(["rating","watching_status","watched_epi
    x_train=target_df_user_final[target_df_user_final.columns[3:-1]]
    y_train=target_df_user_final["Liked"]

    # data normalization with sklearn
    # fit scaler on training data
    # print("NAN check",x_train.isna().any())
    try:
        norm = MinMaxScaler().fit(x_train)
        # transform training data
        x_transformed = norm.transform(x_train)

        """might need to change to other classifier in the future"""
        # logistic classifier
        clf_logistic=LogisticRegression(random_state=42,max_iter=8000) # increase the
        # logistic regression: accuracy
        # score_logistic=cross_val_score(clf_logistic,x_transformed,y_train,cv=5,scori
        # decision tree: accuracy
        # score_log=cross_val_score(clf_logistic,x_transformed,y_train,cv=5,scoring="a
        # print(score_log)
        # confusion matrix
        # pred_log=cross_val_predict(clf_logistic,x_transformed,y_train,cv=5)
        #print(confusion_matrix(y_train,pred_log))

        # fit model
        clf_logistic.fit(x_transformed, y_train)
        # create empty data frame to add on recommended anime for a user
```

```
        rec_df_for_user = pd.DataFrame()
        #print(recommendation_list(i))


        # here to change the number of anime to show: we test 10, 20, 30
        for rec_anime in list(recommendation_list(i))[:10]:
            #print(rec_anime)
            a_row=df_anime_final.loc[df_anime_final["Name"]==rec_anime]
            #print(a_row)
            rec_df_for_user=rec_df_for_user.append(a_row)
            #print(rec_df_for_user)
        #print(rec_df_for_user)
        x_test=rec_df_for_user[['Score', 'Episodes', 'Duration', 'Ranked', 'Popularity
               'Members', 'Favorites', 'Watching', 'Completed', 'On-Hold', 'Dropped',
               'Plan to Watch', 'new_score']]

        x_test_ransformed = norm.transform(x_test)
        test_pred=clf_logistic.predict(x_test_ransformed)
        #print(test_pred)
        pred_y=test_pred.tolist()
        position_containor_cbv.append(pred_y)
        precision_score1=sum(pred_y)/len(pred_y)
        precision_containor.append(precision_score1)
    except Exception as e:
        #print(e)
        pass
```

In [88]:

```
# if we recommend 5 anime per animie a user like, we get like 42% precision
print("avg precision",sum(precision_containor)/len(precision_containor))
```

```
avg precision 0.42045454545454536
```

3.1.1.5 Focused MAP

In [89]:

```
# test accuracy: fix position to 3
pos_three_cbv=[x[:3] for x in position_containor_cbv]
acccuracy_three_cbv=[sum(y)/3 for y in pos_three_cbv]
print("accuracy when only looking at first 3 posistion: ", sum(acccuracy_three_cbv)/le
```

```
accuracy when only looking at first 3 posistion:  0.40909090909090917
```

In [90]:

```
# test accuracy: fix position to 5
pos_five_cbv=[x[:5] for x in position_containor_cbv]
acccuracy_five_cbv=[sum(y)/5 for y in pos_five_cbv]
print("accuracy when only looking at first 5 posistion: ", sum(acccuracy_five_cbv)/len
```

```
accuracy when only looking at first 5 posistion:  0.42500000000000004
```

3.1.2 Vector Space Model (using 'gender'+'synoposis')

In [13…

```
# change from object to string
df_anime_with_synopsis['Genders'] = df_anime_with_synopsis['Genders'].astype('str')
df_anime_with_synopsis['sypnopsis'] = df_anime_with_synopsis['sypnopsis'].astype('str'
```

In [13…

```
# convert each string element to list
all_list=[]
for each_value in df_anime_with_synopsis['Genders']:
    each_list = each_value.split(",")
    # print(each_list)
    # decide to keep the top 3 gender
    each_list = each_list[:3]
    # print(each_list)
    all_list.append(each_list)
```

In [13…
```
# print(all_list)
df_anime_with_synopsis['Genders']=all_list
```

In [13…
```
df_anime_with_synopsis['Genders']
```

Out[138]:
```
0                [Action, Adventure, Comedy]
1                   [Action, Drama, Mystery]
2                [Action, Sci-Fi, Adventure]
3                  [Action, Mystery, Police]
4              [Adventure, Fantasy, Shounen]
                         ...
16209     [Adventure, Mystery, Supernatural]
16210         [Comedy, Horror, Supernatural]
16211            [Mystery, Dementia, Horror]
16212     [Adventure, Slice of Life, Comedy]
16213                      [Action, Fantasy]
Name: Genders, Length: 16214, dtype: object
```

In [13…
```
def get_clear_string():
    clean_list = []
    for i in df_anime_with_synopsis['Genders']:
        clean_list.append(' '.join(i) )

    return clean_list
```

In [14…
```
df_anime_with_synopsis['clean_genders']=get_clear_string()
df_anime_with_synopsis['soup']=df_anime_with_synopsis['clean_genders']+" "+df_anime_w
```

In [14…
```
# Term Frequency-Inverse Document Frequency

# Define a TF-IDF Vectorizer Object. Remove all english stop words such as 'the', 'a'
tfidf_1 = TfidfVectorizer(stop_words='english')

#Construct the required TF-IDF matrix by fitting and transforming the data
tfidf_matrix_1 = tfidf_1.fit_transform(df_anime_with_synopsis['soup'].values.astype('

#Output the shape of tfidf_matrix: we have 45064 different vocabs, with total anime 16
tfidf_matrix_1.shape
```

Out[142]:
```
(16214, 45065)
```

In [14…
```
# Compute the cosine similarity matrix
cosine_sim_1 = linear_kernel(tfidf_matrix_1, tfidf_matrix_1)
```

In [14…
```
#Construct a reverse map of indices and anime titles
indices = pd.Series(df_anime_with_synopsis.index, index=df_anime_with_synopsis['Name'
```

In [14…
```
get_recommendations("Naruto",5,cosine_sim_1)
```

Out[145]:
```
1508                                   Naruto: Shippuuden
11346                       Boruto: Naruto Next Generations
6158              Naruto: Shippuuden Movie 6 - Road to Ninja
3103     Naruto: Shippuuden - Shippuu! "Konoha Gakuen" Den
8831                            Boruto: Naruto the Movie
Name: Name, dtype: object
```

The reason that the 2 methods generate similar results:

TF-IDF takes into consideration the relative frequency of a vocab among different anime. However, the vocab that occurs in every anime is not important to distinguish the documents. For example, genres like action would not make a huge different because it appears in most anime. Since we are choosing 3 genres for each anime, and the total genre types are not very significantly different or distinct between each anime, the resulting of combining gender to synoposis is not that different from the initial methods using synoposis only.

So for later analysis, we will use synoposis only.

3.1.3. Nearest Neighbor Model

Besides utilizing the vector space technique to understand similarities with document angles using anime descriptions, another way to understand similarity is by using Euclidean distance between anime using features other than plain text. Nearest Neighbor algorithm is introduced here as another approach: it finds the k number of points (or anime) closes to a certain data point (or anime).

In [15…

```
# new df with info that we need for knn
df_knn=df_anime_final[["anime_id","Name","new_score","Genders","Type","Episodes","Aire
        "Watching","Completed","On-Hold","Dropped","Plan to Watch"]].copy()
df_knn.head(2)
```

Out[159]:

	anime_id	Name	new_score	Genders	Type	Episodes	Aired	Durati
0	1	Cowboy Bebop	8.740248	Action,Adventure,Comedy,Drama,Sci-Fi,Space	TV	26	1998	
1	5	Cowboy Bebop: Tengoku no Tobira	8.390985	Action,Drama,Mystery,Sci-Fi,Space	Movie	1	2001	

In [16…

```
# select feature
anime_features1=df_knn[["new_score","Episodes","Popularity","Members","Watching","Comp
```

In [16…

```
df_knn.head()
```

Out[161]:

	anime_id	Name	new_score	Genders	Type	Episodes	Aire
0	1	Cowboy Bebop	8.740248	Action,Adventure,Comedy,Drama,Sci-Fi,Space	TV	26	19
1	5	Cowboy Bebop: Tengoku no Tobira	8.390985	Action,Drama,Mystery,Sci-Fi,Space	Movie	1	20
2	6	Trigun	8.215289	Action,Sci-Fi,Adventure,Comedy,Drama,Shounen	TV	26	19
3	7	Witch Hunter Robin	7.216657	Action,Mystery,Police,Supernatural,Drama,Magic	TV	26	20

	anime_id	Name	new_score	Genders	Type	Episodes	Aire
4	8	Bouken Ou Beet	6.892115	Adventure,Fantasy,Shounen,Supernatural	TV	52	20(

In [16…

```
# featrues already for knn
anime_features=pd.concat([anime_features1,
                          df_knn["Genders"].str.get_dummies(sep=","),
                          pd.get_dummies(df_knn["Type"]),
                          pd.get_dummies(df_knn["Rating"])],axis=1)
anime_features.head()
```

Out[162]:

	new_score	Episodes	Popularity	Members	Watching	Completed	On-Hold	Dropped	Plan to Watch	Act
0	8.740248	26	39	1251960	105808	718161	71513	26678	329800	
1	8.390985	1	518	273145	4143	208333	1935	770	57964	
2	8.215289	26	201	558913	29113	343492	25465	13925	146918	
3	7.216657	26	1467	94683	4300	46165	5121	5378	33719	
4	6.892115	52	4369	13224	642	7314	766	1108	3394	

In [16…

```
# scaling

min_max_scaler = MinMaxScaler()
anime_features = min_max_scaler.fit_transform(anime_features)
```

In [16…

```
# it is just the first step of knn, thus not a supervised learning task
# here we recommend 5 anime, n_neighbor=6
nbrs = NearestNeighbors(n_neighbors=6, algorithm='ball_tree').fit(anime_features)

distances, indexes = nbrs.kneighbors(anime_features)
```

In [16…

```
def get_index_from_name(name):
    return df_knn[df_knn["Name"]==name].index.tolist()[0]


all_anime_names = list(df_knn.Name.values)
```

In [16…

```
# search for similar animes both by name
def print_similar_animes(name=None):
    found_id = get_index_from_name(name)
    anime_list_rec=[]
    for id_in in indexes[found_id][1:]:
        anime_list_rec.append(df_knn.loc[id_in]["Name"])
    return anime_list_rec
```

In [16…

```
print_similar_animes("Naruto")
```

Out[167]:

```
['Naruto: Shippuuden',
 'Dragon Ball Z',
```

```
'Dragon Ball Super',
'Boruto: Naruto Next Generations',
'Dragon Ball Kai']
```

In [16…

```
# get recommendation list for a user
def recommendation_list_knn(user_id):
    list_to_walk_thr=relevant_anime_for_user(user_id)
    #print(list_to_walk_thr)
    rec_list =[]
    count=0
    for anime in list_to_walk_thr:
        try:
            alist=print_similar_animes(anime)
            rec_list.append(alist)
        # handle errors
        except:
            #print("failed")
            pass
    #print(count)
    #print(rec_list)
    flattened_list = [val for sublist in rec_list for val in sublist]
    # print(len(flattened_list),"anime has been recommended")
    # set removes duplicaed recommendations
    return set(flattened_list)
```

3.1.3.1 MAP

In [10…

```
precision_containor_knn=[]
position_containor_nn=[]
for i in range(100):
    target_df_user=anime_features_for_each_user.loc[anime_features_for_each_user["use
    # drop air since it has nan, drop rating, watching statues and episodes since thes
    target_df_user_final=target_df_user.drop(["rating","watching_status","watched_epi
    x_train=target_df_user_final[target_df_user_final.columns[3:-1]]
    y_train=target_df_user_final["Liked"]

    # data normalization with sklearn
    # fit scaler on training data
    # print("NAN check",x_train.isna().any())
    try:
        norm = MinMaxScaler().fit(x_train)
        # transform training data
        x_transformed = norm.transform(x_train)

        """might need to change to other classifier in the future"""
        # logistic classifier
        clf_logistic=LogisticRegression(random_state=42,max_iter=8000) # increase the
        # logistic regression: accuracy
        # score_logistic=cross_val_score(clf_logistic,x_transformed,y_train,cv=5,scori
        # decision tree: accuracy
        # score_log=cross_val_score(clf_logistic,x_transformed,y_train,cv=5,scoring="a
        # print(score_log)
        # confusion matrix
        # pred_log=cross_val_predict(clf_logistic,x_transformed,y_train,cv=5)
        #print(confusion_matrix(y_train,pred_log))

        # fit model
        clf_logistic.fit(x_transformed, y_train)
        # create empty data frame to add on recommended anime for a user
        rec_df_for_user = pd.DataFrame()
        #print(recommendation_list(i))
        for rec_anime in list(recommendation_list_knn(i))[:10]:
            #print(rec_anime)
            a_row=df_anime_final.loc[df_anime_final["Name"]==rec_anime]
            #print(a_row)
```

```
            rec_df_for_user=rec_df_for_user.append(a_row)
            #print(rec_df_for_user)
        #print(rec_df_for_user)
        x_test=rec_df_for_user[['Score', 'Episodes', 'Duration', 'Ranked', 'Popularity
               'Members', 'Favorites', 'Watching', 'Completed', 'On-Hold', 'Dropped',
               'Plan to Watch', 'new_score']]

        x_test_ransformed = norm.transform(x_test)
        test_pred=clf_logistic.predict(x_test_ransformed)
        #print(test_pred)
        pred_y=test_pred.tolist()
        position_containor_nn.append(pred_y)
        precision_score2=sum(pred_y)/len(pred_y)
        precision_containor_knn.append(precision_score2)
    except Exception as e:
        #print(e)
        pass
```

In [10…

```
# if we recommend 1 anime per animie a user like, we get like 56% precision
print("avg precision",sum(precision_containor_knn)/len(precision_containor_knn))
print("active sample users are:",len(precision_containor_knn))
```

```
avg precision 0.5045454545454544
active sample users are: 88
```

3.1.3.2 Focused MAP

In [10…

```
# test accuracy: fix position to 3
pos_three_nn=[x[:3] for x in position_containor_nn]
acccuracy_three_nn=[sum(y)/3 for y in pos_three_nn]
print("accuracy when only looking at first 3 posistion: ", sum(acccuracy_three_nn)/ler
```

```
accuracy when only looking at first 3 posistion:  0.4621212121212121
```

In [10…

```
# test accuracy: fix position to 5
pos_five_nn=[x[:5] for x in position_containor_nn]
acccuracy_five_nn=[sum(y)/5 for y in pos_five_nn]
print("accuracy when only looking at first 5 posistion: ", sum(acccuracy_five_nn)/len
```

```
accuracy when only looking at first 5 posistion:  0.4840909090909092
```

3.2 Collaborative Filtering

3.2.1. User-based Collaborative Filtering

As its name suggests, user-based approach first understands the similarity between users. Then, the anime which scores high among top N similar users will be recommended. The below section will illustrate the rationale behind thoroughly.

In [10…

```
# the dataset we use here
df_animelist.head()
```

Out[105]:

	user_id	anime_id	rating	watching_status	watched_episodes
0	0	67	9	1	1
1	0	6702	7	1	4
2	0	242	10	1	4
3	0	4898	0	1	1
4	0	21	10	1	0

In [10…
```
df_animelist["rating"].value_counts()
```

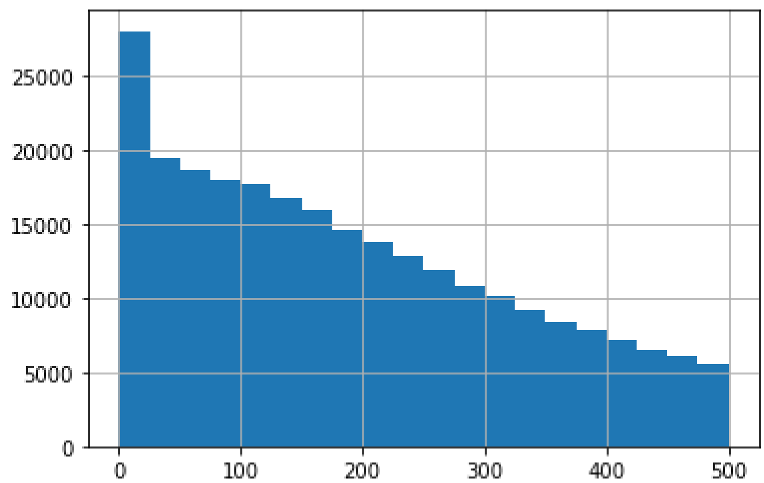
Out[106]:
```
0     46827035
8     15422150
7     14244633
9     10235934
6      7543377
10     7144392
5      4029645
4      1845854
3       905700
2       545339
1       480688
Name: rating, dtype: int64
```

In [10…
```
# check avg number of rating per user
import statistics
ratings_per_user = df_animelist.groupby('user_id')['rating'].count()
statistics.mean(ratings_per_user.tolist())
```

Out[107]: 335.2817846947233

In [10…
```
# distribution of ratings per user: many rating less than 100 anime
ratings_per_user.hist(bins=20, range=(0,500))
```

Out[108]: <AxesSubplot:>



In [10…
```
### use only the first 100 users only (for precision analysis)
first_1000_idx=df_animelist.loc[df_animelist["user_id"]==1000].index[0]
df_animelist_first1000=df_animelist[:first_1000_idx]
```

In [11…
```
# Matrix: # of rows users; # of columns for anime
rating_matrix = df_animelist_first1000.pivot_table(index='user_id', columns='anime_id
# replace NaN values with 0
rating_matrix = rating_matrix.fillna(0)
# display the top few rows
rating_matrix.head(10)
```

Out[110]:

anime_id	1	5	6	7	8	15	16	17	18	19	20	21	22	23	24	25	26	27	28
user_id																			
0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	10.0	0.0	0.0	9.0	0.0	0.0	0.0	0.0
1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	9.0	10.0	9.0	9.0	0.0	0.0	0.0	0.0	0.0	0.0
2	0.0	0.0	0.0	0.0	0.0	9.0	0.0	0.0	0.0	0.0	9.0	9.0	9.0	0.0	0.0	0.0	0.0	0.0	0.0
3	9.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	8.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

anime_id	1	5	6	7	8	15	16	17	18	19	20	21	22	23	24	25	26	27	28
user_id																			
4	0.0	0.0	0.0	0.0	0.0	0.0	9.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
5	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	10.0	0.0	0.0	0.0	0.0
6	6.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	5.0	0.0	5.0	0.0	0.0	0.0	0.0	0.0	0.0
7	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
8	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
9	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

In [11…

```
# find similar users using cosine similarity
from sklearn.metrics.pairwise import cosine_similarity
import operator
# find the top 3 similar users by cosine similarity
def similar_users(user_id, matrix, k=3):
    # create a df of just the current user
    user = matrix[matrix.index == user_id]

    # and a df of all other users
    other_users = matrix[matrix.index != user_id]

    # calc cosine similarity between user and each other user
    similarities = cosine_similarity(user,other_users)[0].tolist()

    # create list of indices of these users
    indices = other_users.index.tolist()

    # create key/values pairs of user index and their similarity
    index_similarity = dict(zip(indices, similarities))

    # sort by similarity
    index_similarity_sorted = sorted(index_similarity.items(), key=operator.itemgette
    index_similarity_sorted.reverse()

    # grab k users off the top
    top_users_similarities = index_similarity_sorted[:k]
    #print(top_users_similarities)
    users = [u[0] for u in top_users_similarities]
    indices_u=[u[1] for u in top_users_similarities]

    return users,indices_u
```

In [11…

```
# test this for user 0
current_user=0
similar_user_indices = similar_users(current_user, rating_matrix,3)
print(similar_user_indices)
```

```
([521, 530, 247], [0.28358645668342636, 0.21902816515890028, 0.21279261377905342])
```

In [11…

```
# recommendation example: 5 neighbors
def recommend_item_cf_user_5(user_index, similar_user_indices, matrix, items=10):

    # load vectors for similar users
    similar_users = matrix[matrix.index.isin(similar_user_indices[0])]
    similar_users=pd.DataFrame(similar_users, index=[similar_user_indices[0][0],simil
                                                      similar_user_indices[0][3],similar
    #real_dis=[(1-x) for x in similar_user_indices[1]]
    total_distance=sum(similar_user_indices[1])
```

```
    #print(similar_users)
    #print(total_distance)
    dis_div_total_distance=[x/total_distance for x in similar_user_indices[1]]
    dis_div_total_distance = Series({similar_user_indices[0][0]:dis_div_total_distance
                  similar_user_indices[0][1]:dis_div_total_distance[1],
                  similar_user_indices[0][2]:dis_div_total_distance[2],
                                   similar_user_indices[0][3]:dis_div_total_distance[
                                   similar_user_indices[0][4]:dis_div_total_distance[
    #print(dis_div_total_distance)
    # calc weighted avg ratings across the 3 similar users
    #print(type(similar_users))
    similar_users = similar_users.mul(dis_div_total_distance,axis=0)
    #print(similar_users)
    similar_users = similar_users.sum(axis=0)
    # convert to dataframe so its easy to sort and filter
    similar_users_df = pd.DataFrame(similar_users, columns=['mean'])
    #print(similar_users_df)

    # load vector for the current user
    user_df = matrix[matrix.index == user_index]
    # transpose it so its easier to filter
    user_df_transposed = user_df.transpose()
    # rename the column as 'rating'
    user_df_transposed.columns = ['rating']
    # remove any rows without a 0 value. Anime not watched yet
    user_df_transposed = user_df_transposed[user_df_transposed['rating']==0]
    # generate a list of animes the user has not seen
    animes_unseen = user_df_transposed.index.tolist()

    # filter avg ratings of similar users for only anime the current user has not seer
    similar_users_df_filtered = similar_users_df[similar_users_df.index.isin(animes_u
    # order the dataframe
    similar_users_df_ordered = similar_users_df.sort_values(by=['mean'], ascending=Fa
    # grab the top n anime
    top_n_anime = similar_users_df_ordered.head(items)
    top_n_anime_indices = top_n_anime.index.tolist()
    # lookup these anime in the other dataframe to find names
    anime_information = df_anime_final[df_anime_final['anime_id'].isin(top_n_anime_in

    return anime_information["Name"] #items
```

In [11…

```
# combined function to output recommended top 5 anime
def find_anime_cf_user(user_id,k,output_n): # k = number of similar users; output_n =
    similar_user_indices=similar_users(user_id, rating_matrix, k) # k= number of simi
    # item = number of anime to recommend
    output_anime=recommend_item_cf_user_5(user_id, similar_user_indices, rating_matri
    return output_anime
```

In [11…

```
# print top 10 recommendation when choosing 5 neighbors
find_anime_cf_user(0,5,10)
```

Out[115]:

```
100              Fullmetal Alchemist
142                    Mononoke Hime
176       Sen to Chihiro no Kamikakushi
202                       Elfen Lied
404                Howl no Ugoku Shiro
537           Kaze no Tani no Nausicaä
1393                      Death Note
1535              Byousoku 5 Centimeter
2049              Toki wo Kakeru Shoujo
2646                Gake no Ue no Ponyo
Name: Name, dtype: object
```

3.2.1.1 MAP

In [11…

```
precision_containor_cf_user=[]
position_containor_ub=[]
for i in range(100):
    target_df_user=anime_features_for_each_user.loc[anime_features_for_each_user["use
    # drop air since it has nan, drop rating, watching statues and episodes since thes
    target_df_user_final=target_df_user.drop(["rating","watching_status","watched_epi
    x_train=target_df_user_final[target_df_user_final.columns[3:-1]]
    y_train=target_df_user_final["Liked"]

    # data normalization with sklearn
    # fit scaler on training data
    # print("NAN check",x_train.isna().any())

    try:
        norm = MinMaxScaler().fit(x_train)
        # transform training data
        x_transformed = norm.transform(x_train)
        # logistic classifier
        clf_logistic=LogisticRegression(random_state=42,max_iter=8000) # increase the
        # logistic regression: accuracy
        # score_logistic=cross_val_score(clf_logistic,x_transformed,y_train,cv=5,scori
        # decision tree: accuracy
        # score_log=cross_val_score(clf_logistic,x_transformed,y_train,cv=5,scoring="a
        # print(score_log)
        # confusion matrix
        # pred_log=cross_val_predict(clf_logistic,x_transformed,y_train,cv=5)
        #print(confusion_matrix(y_train,pred_log))

        # fit model

        clf_logistic.fit(x_transformed, y_train)
        # create empty data frame to add on recommended anime for a user
        rec_df_for_user = pd.DataFrame()
        #print(recommendation_list(i))
        for rec_anime in find_anime_cf_user(i,5,30): # number of neighbors, number of
            #print(rec_anime)
            a_row=df_anime_final.loc[df_anime_final["Name"]==rec_anime]
            #print(a_row)
            rec_df_for_user=rec_df_for_user.append(a_row)
            #print(rec_df_for_user)
        #print(rec_df_for_user)
        x_test=rec_df_for_user[['Score', 'Episodes', 'Duration', 'Ranked', 'Popularity
             'Members', 'Favorites', 'Watching', 'Completed', 'On-Hold', 'Dropped',
             'Plan to Watch', 'new_score']]

        x_test_transformed = norm.transform(x_test)
        test_pred=clf_logistic.predict(x_test_transformed)
        # print(test_pred)
        pred_y=test_pred.tolist()
        position_containor_ub.append(pred_y)
        precision_score3=sum(pred_y)/len(pred_y)
        precision_containor_cf_user.append(precision_score3)

    except Exception as e:
        #print(e)
        pass
```

In [11…

```
print("avg precision",sum(precision_containor_cf_user)/len(precision_containor_cf_user
print("active sample users are:",len(precision_containor_cf_user))
```

```
avg precision 0.740909090909091
active sample users are: 88
```

3.2.1.2 MAP

In [11⋯

```
# test accuracy: fix position to 3
pos_three_ub=[x[:3] for x in position_containor_ub]
acccuracy_three_ub=[sum(y)/3 for y in pos_three_ub]
print("accuracy when only looking at first 3 posistion: ", sum(acccuracy_three_ub)/ler
```

```
accuracy when only looking at first 3 posistion:  0.7613636363636364
```

In [12⋯

```
# test accuracy: fix position to 5
pos_five_ub=[x[:5] for x in position_containor_ub]
acccuracy_five_ub=[sum(y)/5 for y in pos_five_ub]
print("accuracy when only looking at first 5 posistion: ", sum(acccuracy_five_ub)/len
```

```
accuracy when only looking at first 5 posistion:  0.7477272727272729
```

3.2.2 Item-based Collaborative Filtering

This technique, instead of finding similar users, would find similar items or anime. In this method, the ratings by a user of all unrated anime is predicted by finding the top N similar anime that have been rated by this user. In short, the rating of unrated anime by a user is determined by historical ratings of similar anime rated by that user. If user A has rated anime 1 and anime 2, now the task is to predict rating of anime 3. The rating of anime 3 by this user would likely be the rating of anime 2 if that anime 2 is deemed more similar to anime 3 than anime 1 is.

In [12⋯

```
# again, using only the first 1000 users as data
# Matrix: # of rows users; # of columns for anime
rating_matrix_item = df_animelist_first1000.pivot_table(index='user_id', columns='ani
# replace NaN values with 0
rating_matrix_item = rating_matrix_item.fillna(0)
# display the top few rows
#rating_matrix_item.head(10)
```

In [12⋯

```
# transpose the crosstab
rating_matrix_item = rating_matrix_item.T
```

In [12⋯

```
rating_matrix_item.head()
```

Out[123]:

user_id	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
anime_id																			
1	0.0	0.0	0.0	9.0	0.0	0.0	6.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	9.0	0.0	0.0	0.0	8.0
5	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	10.0
6	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
7	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
8	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	10.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

In [12⋯

```
def recommend_anime_item(user, number_neighbors,num_recommended_anime):
    # copy df
    df1 = rating_matrix_item.copy()

    # find the nearest neighbors using NearestNeighbors(n_neighbors=3)
    number_neighbors = number_neighbors
    knn_item = NearestNeighbors(metric='cosine', algorithm='brute')
    knn_item.fit(rating_matrix_item.values)
```

```
    distances_item, indices_item = knn_item.kneighbors(rating_matrix_item.values, n_n
    #print(distances_item)
    # convert user_name to user_index for user_id
    user_index = rating_matrix_item.columns.tolist().index(user)
    #print(user_index)

    # t: anime_title, m: the row number of t in df
    for m,t in list(enumerate(rating_matrix_item.index)):

      # find anime without ratings by user_id
        if rating_matrix_item.iloc[m, user_index] == 0:
            sim_anime = indices_item[m].tolist()
            anime_distances = distances_item[m].tolist()

            if m in sim_anime:
                id_anime = sim_anime.index(m)
                sim_anime.remove(m)
                anime_distances.pop(id_anime)

            else:
                sim_anime = sim_anime[:number_neighbors-1]
                anime_distances = anime_distances[:number_neighbors-1]

            # anime_similarty = 1 - anime_distance
            anime_similarity = [1-x for x in anime_distances]
            anime_similarity_copy = anime_similarity.copy()
            nominator = 0

        # for each similar anime
            for s in range(0, len(anime_similarity)):

                # check if the rating of a similar movie is zero
                if rating_matrix_item.iloc[sim_anime[s], user_index] == 0:

                    # if the rating is zero, ignore the rating and the similarity in c
                    if len(anime_similarity_copy) == (number_neighbors - 1):
                        anime_similarity_copy.pop(s)

                    else:
                        anime_similarity_copy.pop(s-(len(anime_similarity)-len(anime_

                  # if the rating is not zero, use the rating and similarity in the ca
                else:
                    nominator = nominator + anime_similarity[s]*rating_matrix_item.il

            # check if the number of the ratings with non-zero is positive
            if len(anime_similarity_copy) > 0:

              # check if the sum of the ratings of the similar anime is positive.
                if sum(anime_similarity_copy) > 0:
                    predicted_r = nominator/sum(anime_similarity_copy)

              # Even if there are some anime for which the ratings are positive,
            # some anime have zero similarity even though they are selected as similar
              # in this case, the predicted rating becomes zero as well
                else:
                    predicted_r = 0

            # if all the ratings of the similar anime are zero, then predicted rating
            else:
                predicted_r = 0

      # place the predicted rating into the copy of the original dataset
            df1.iloc[m,user_index] = predicted_r
```

```
    for m in rating_matrix_item[rating_matrix_item[user] > 0][user].index.tolist():
    #print(m)
        pass
    #print('\n')
    recommended_anime = []

    for m in rating_matrix_item[rating_matrix_item[user] == 0].index.tolist():

        index_df = rating_matrix_item.index.tolist().index(m)
        predicted_rating = df1.iloc[index_df, df1.columns.tolist().index(user)]
        recommended_anime.append((m, predicted_rating))

    sorted_rm = sorted(recommended_anime, key=lambda x:x[1], reverse=True)

    #print('The list of the Recommended Anime \n')
    rank = 1
    anime_id_container=[]
    for recommended_anime in sorted_rm[:num_recommended_anime]:

        #print('{}: {} - predicted rating:{}'.format(rank, recommended_anime[0], recom
        anime_id_container.append(recommended_anime[0])
        rank = rank + 1
    anime_information_item = df_anime_final[df_anime_final['anime_id'].isin(anime_id_

    return anime_information_item["Name"]
```

In [12…

```
print(recommend_anime_item(0,10,15))
```

```
2                                      Trigun
17                              Trinity Blood
26       Rurouni Kenshin: Meiji Kenkaku Romantan
40                                    Chobits
128                                    Blood+
409                              Perfect Blue
452                  Yu☆Gi☆Oh!: Duel Monsters GX
833                                   Gintama
1230           Final Fantasy: The Spirits Within
2382                              Shinreigari
3416                           Yu☆Gi☆Oh! 5D's
3524                 One Piece Film: Strong World
5107                       Shinrei Tantei Yakumo
5246                            Colorful (Movie)
7492                    Kaguya-hime no Monogatari
Name: Name, dtype: object
```

3.2.2.1 MAP

In [12…

```
precision_containor_cf_item=[]
position_container_it=[]
for i in range(100):
    target_df_user=anime_features_for_each_user.loc[anime_features_for_each_user["use
    # drop air since it has nan, drop rating, watching statues and episodes since thes
    target_df_user_final=target_df_user.drop(["rating","watching_status","watched_epi
    x_train=target_df_user_final[target_df_user_final.columns[3:-1]]
    y_train=target_df_user_final["Liked"]

    # data normalization with sklearn
    # fit scaler on training data
    # print("NAN check",x_train.isna().any())

    try:
        norm = MinMaxScaler().fit(x_train)
        # transform training data
        x_transformed = norm.transform(x_train)
        # logistic classifier
```

```
        clf_logistic=LogisticRegression(random_state=42,max_iter=8000) # increase the
        # logistic regression: accuracy
        # score_logistic=cross_val_score(clf_logistic,x_transformed,y_train,cv=5,scori
        # decision tree: accuracy
        # score_log=cross_val_score(clf_logistic,x_transformed,y_train,cv=5,scoring="a
        # print(score_log)
        # confusion matrix
        # pred_log=cross_val_predict(clf_logistic,x_transformed,y_train,cv=5)
        #print(confusion_matrix(y_train,pred_log))

        # fit model

        clf_logistic.fit(x_transformed, y_train)
        # create empty data frame to add on recommended anime for a user
        rec_df_for_user = pd.DataFrame()
        #print(recommendation_list(i))
        for rec_anime in recommend_anime_item(i,5,10).tolist():
            #print(rec_anime)
            a_row=df_anime_final.loc[df_anime_final["Name"]==rec_anime]
            #print(a_row)
            rec_df_for_user=rec_df_for_user.append(a_row)
            #print(rec_df_for_user)
        #print(rec_df_for_user)
        x_test=rec_df_for_user[['Score', 'Episodes', 'Duration', 'Ranked', 'Popularity
               'Members', 'Favorites', 'Watching', 'Completed', 'On-Hold', 'Dropped',
               'Plan to Watch', 'new_score']]

        x_test_transformed = norm.transform(x_test)
        test_pred=clf_logistic.predict(x_test_transformed)
        #print(test_pred)
        pred_y=test_pred.tolist()
        position_container_it.append(pred_y)
        precision_score4=sum(pred_y)/len(pred_y)
        precision_containor_cf_item.append(precision_score4)

    except Exception as e:
        #print(e)
        pass
```

In [12…

```
# when recommending 5 anime for each user, we get precision scrore of like 62%
print("avg precision",sum(precision_containor_cf_item)/len(precision_containor_cf_iter
print("active sample users are:",len(precision_containor_cf_item))
```

```
avg precision 0.5942148760330578
active sample users are: 88
```

3.2.2.2 Focused MAP

In [12…

```
# test accuracy: fix position to 3
pos_three_it=[x[:3] for x in position_container_it]
acccuracy_three_it=[sum(y)/3 for y in pos_three_it]
print("accuracy when only looking at first 3 posistion: ", sum(acccuracy_three_it)/ler
```

```
accuracy when only looking at first 3 posistion:  0.5984848484848484
```

In [12…

```
# test accuracy: fix position to 5
pos_five_it=[x[:5] for x in position_container_it]
acccuracy_five_it=[sum(y)/5 for y in pos_five_it]
print("accuracy when only looking at first 5 posistion: ", sum(acccuracy_five_it)/len
```

```
accuracy when only looking at first 5 posistion:  0.6022727272727275
```

4. MAP: Model Comparison & Visualization

Mean Average Precision (MAP) was calculated in previous sections after each model was built. Here, this section summaries the results of model performance. The inputted values are true results after running each variable combinations of each model. For efficiency consideration, only resuling values are put here.

4.1 MAP: Content-based Vector Space Model

In [13…

```
# map values are generated from above evaluation funciton and recorded
map_5_cbv=[0.50227,0.47727,0.45227,0.4477,0.42727]
map_10_cbv=[0.492045,0.45,0.4284,0.43068,0.41818]
map_15_cbv=[0.50757,0.44756,0.423484,0.42803,0.41363]
map_20_cbv=[0.51515,0.45836,0.431279,0.4244,0.4176]
map_25_cbv=[0.51619,0.459383,0.43559,0.426363,0.41818]
map_30_cbv=[0.51293,0.45968,0.4366,0.42352,0.4208]

x_axis_cbv=['1','3','5','7','10']
```

In [13…

```
# round all to 3 decimal points
map_5_cbv=[round(x,3) for x in map_5_cbv]
map_10_cbv=[round(x,3) for x in map_10_cbv]
map_15_cbv=[round(x,3) for x in map_15_cbv]
map_20_cbv=[round(x,3) for x in map_20_cbv]
map_25_cbv=[round(x,3) for x in map_25_cbv]
map_30_cbv=[round(x,3) for x in map_30_cbv]
```

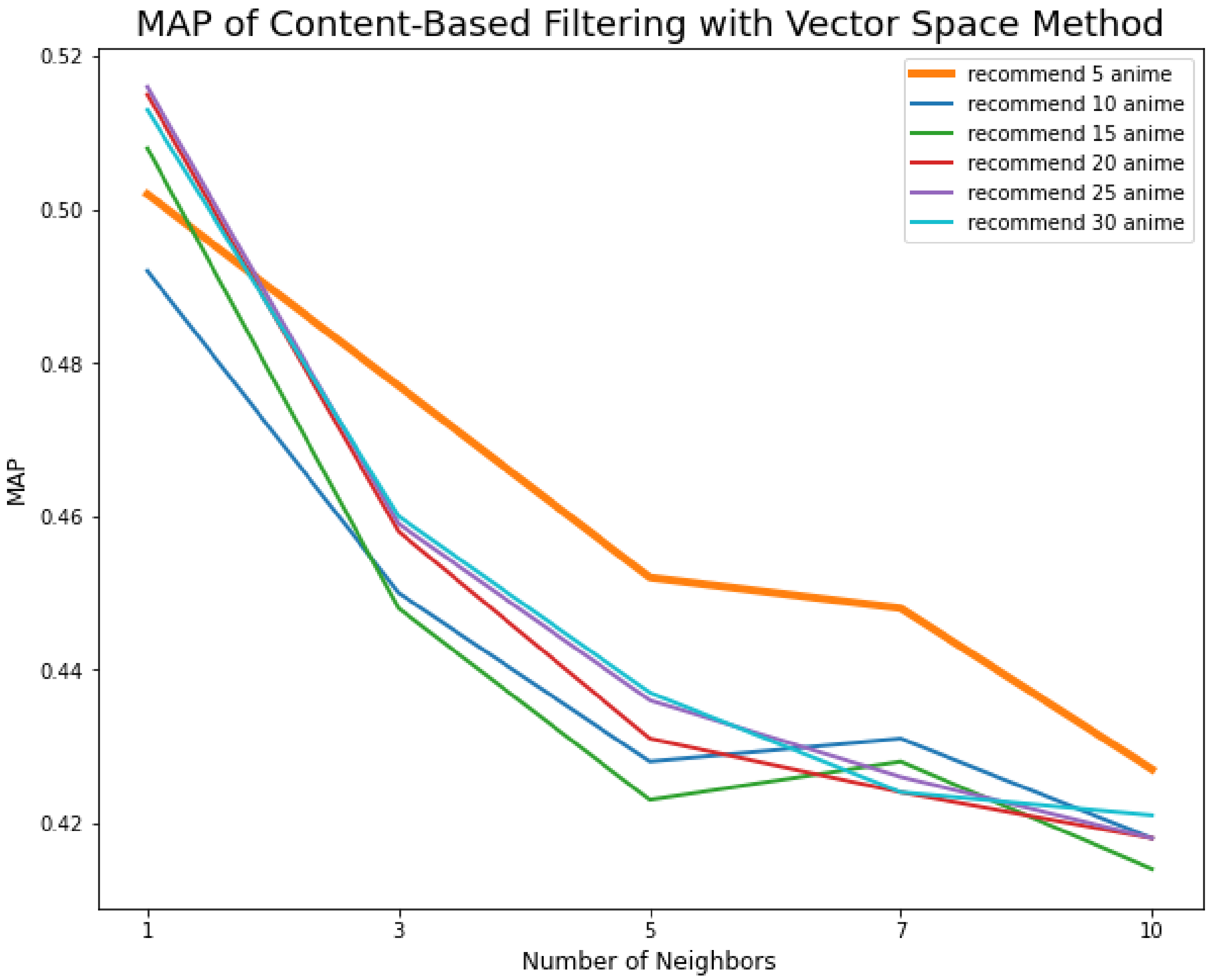
In [13…

```
# Data
df=pd.DataFrame({'x_values': x_axis_cbv, 'y1_values': map_5_cbv, 'y2_values': map_10_(
                'y4_values':map_20_cbv,'y5_values':map_25_cbv,'y6_values':map_30_cbv})
# fig size
plt.figure(figsize=(10,8))
# multiple line plots
plt.plot( 'x_values', 'y1_values', data=df, marker='', color='tab:orange', linewidth=
plt.plot( 'x_values', 'y2_values', data=df, marker='', color='tab:blue', linewidth=2,
plt.plot( 'x_values', 'y3_values', data=df, marker='', color='tab:green', linewidth=2
plt.plot( 'x_values', 'y4_values', data=df, marker='', color='tab:red', linewidth=2,l
plt.plot( 'x_values', 'y5_values', data=df, marker='', color='tab:purple', linewidth=
plt.plot( 'x_values', 'y6_values', data=df, marker='', color='tab:cyan', linewidth=2,

# set x axis label
plt.xlabel('Number of Neighbors',fontsize=12)
# Set the y axis label
plt.ylabel('MAP',fontsize=12)
# Set a title of the current axes.
plt.title('MAP of Content-Based Filtering with Vector Space Method',fontsize=18)

# show legend
plt.legend()

# show graph
plt.show()
```



4.2 MAP: Content-based NN Model

In [13…

```
# map values are generated from above evaluation funciton and recorded
map_5_cbn=[0.57196,0.52727,0.5181,0.479545,0.48863]
map_10_cbn=[0.54924,0.5409,0.509,0.48295,0.48522]
map_15_cbn=[0.54696,0.5336,0.51136,0.4856,0.48863]
map_20_cbn=[0.54981,0.53343,0.5164,0.49545,0.484659]
map_25_cbn=[0.55562,0.536047,0.51776,0.49967,0.49454]
map_30_cbn=[0.55767,0.536653,0.51935,0.50247,0.4928]

x_axis_cbv=['1','3','5','7','10']
```

In [13…

```
# round all to 3 decimal points
map_5_cbn=[round(x,3) for x in map_5_cbn]
map_10_cbn=[round(x,3) for x in map_10_cbn]
map_15_cbn=[round(x,3) for x in map_15_cbn]
map_20_cbn=[round(x,3) for x in map_20_cbn]
map_25_cbn=[round(x,3) for x in map_25_cbn]
map_30_cbn=[round(x,3) for x in map_30_cbn]
```

In [13…

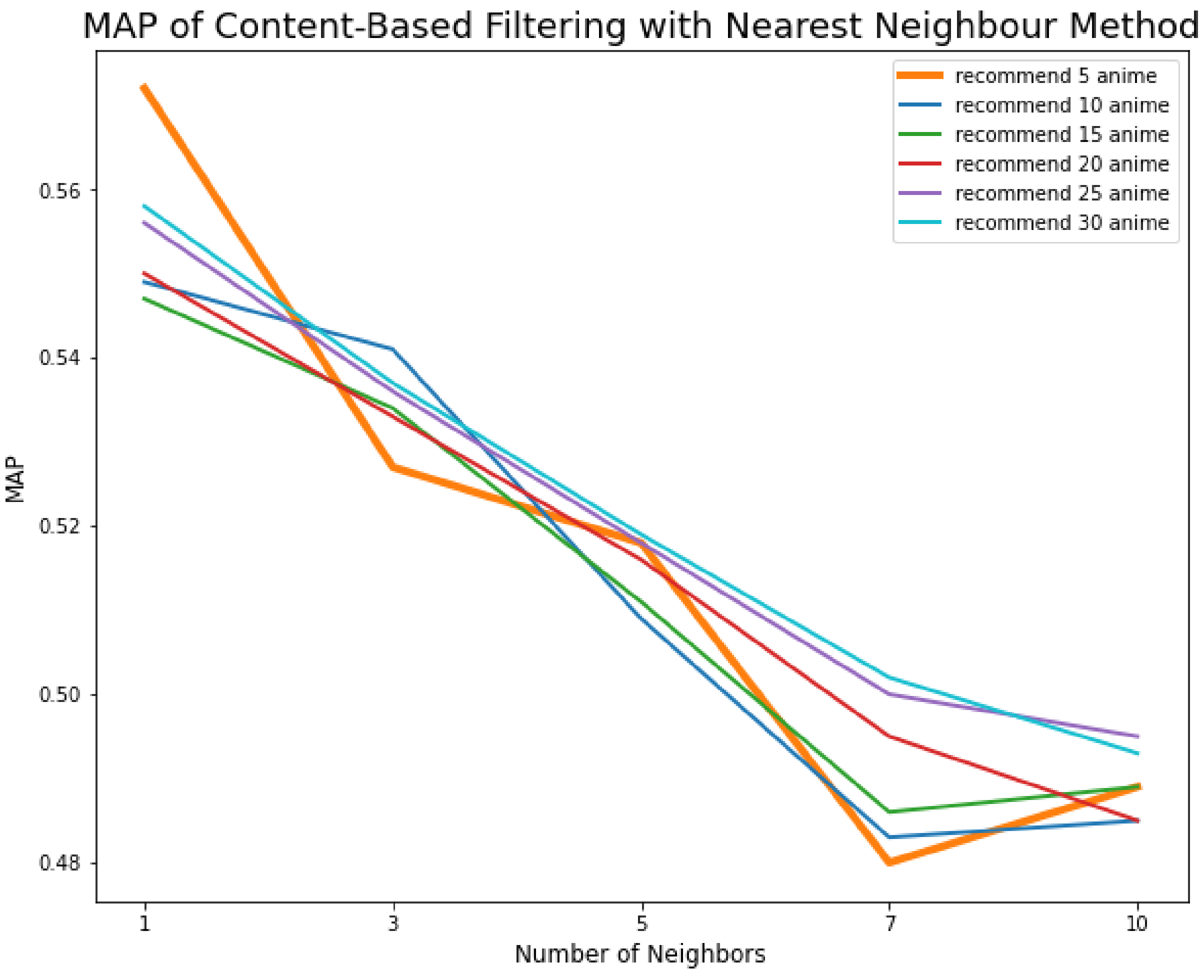
```
# Data
df1=pd.DataFrame({'x_values': x_axis_cbv, 'y1_values': map_5_cbn, 'y2_values': map_10_
                'y4_values':map_20_cbn,'y5_values':map_25_cbn,'y6_values':map_30_cbn})
# fig size
plt.figure(figsize=(10,8))
# multiple line plots
plt.plot( 'x_values', 'y1_values', data=df1, marker='', color='tab:orange', linewidth
plt.plot( 'x_values', 'y2_values', data=df1, marker='', color='tab:blue', linewidth=2
plt.plot( 'x_values', 'y3_values', data=df1, marker='', color='tab:green', linewidth=
plt.plot( 'x_values', 'y4_values', data=df1, marker='', color='tab:red', linewidth=2,
plt.plot( 'x_values', 'y5_values', data=df1, marker='', color='tab:purple', linewidth
```

```
plt.plot( 'x_values', 'y6_values', data=df1, marker='', color='tab:cyan', linewidth=2

# set x axis label
plt.xlabel('Number of Neighbors',fontsize=12)
# Set the y axis label
plt.ylabel('MAP',fontsize=12)
# Set a title of the current axes.
plt.title('MAP of Content-Based Filtering with Nearest Neighbour Method',fontsize=18)

# show legend
plt.legend()

# show graph
plt.show()
```



4.3 MAP: User-based Collaborative Filtering Model

In [13…

```
# map values are generated from above evaluation funciton and recorded
map_5_ub=[0.68538,0.7681,0.78181,0.781818,0.7999]
map_10_ub=[0.68446,0.75,0.767,0.76818,0.78409]
map_15_ub=[0.684174,0.74394,0.75833,0.767424,0.7689]
map_20_ub=[0.67899,0.7392,0.75113,0.75738,0.7585]
map_25_ub=[0.67,0.7309,0.74636,0.7445,0.75181]
map_30_ub=[0.66748,0.726906,0.7409,0.7409,0.74962]

x_axis_ub=['1','3','5','7','10']
```

In [13…

```
# round all to 3 decimal points
map_5_ub=[round(x,3) for x in map_5_ub]
map_10_ub=[round(x,3) for x in map_10_ub]
map_15_ub=[round(x,3) for x in map_15_ub]
map_20_ub=[round(x,3) for x in map_20_ub]
```

```
map_25_ub=[round(x,3) for x in map_25_ub]
map_30_ub=[round(x,3) for x in map_30_ub]
```

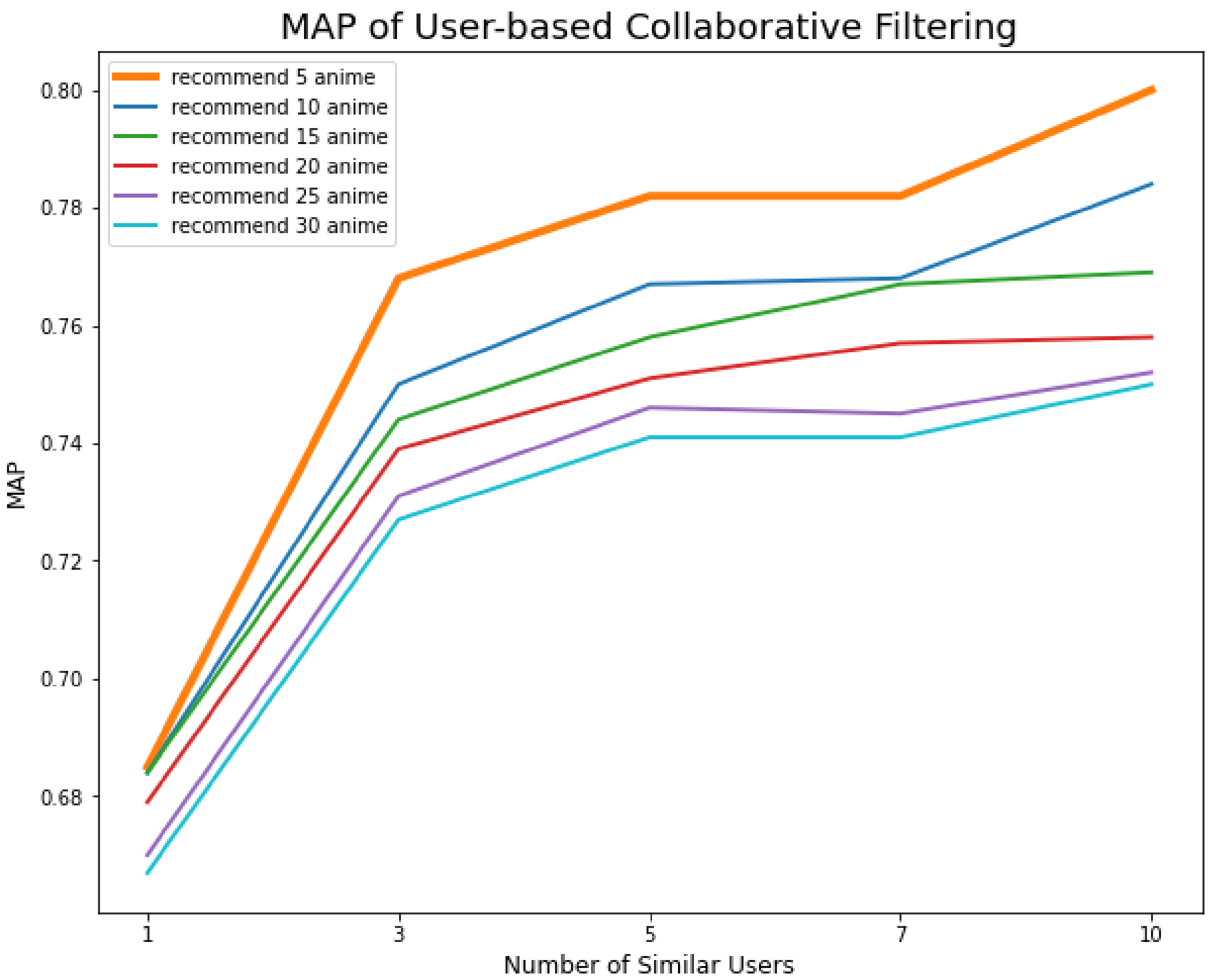
In [14…

```
# Data
df2=pd.DataFrame({'x_values': x_axis_cbv, 'y1_values': map_5_ub, 'y2_values': map_10_u
                'y4_values':map_20_ub,'y5_values':map_25_ub,'y6_values':map_30_ub})
# fig sizeub
plt.figure(figsize=(10,8))
# multiple line plots
plt.plot( 'x_values', 'y1_values', data=df2, marker='', color='tab:orange', linewidth
plt.plot( 'x_values', 'y2_values', data=df2, marker='', color='tab:blue', linewidth=2
plt.plot( 'x_values', 'y3_values', data=df2, marker='', color='tab:green', linewidth=
plt.plot( 'x_values', 'y4_values', data=df2, marker='', color='tab:red', linewidth=2,
plt.plot( 'x_values', 'y5_values', data=df2, marker='', color='tab:purple', linewidth
plt.plot( 'x_values', 'y6_values', data=df2, marker='', color='tab:cyan', linewidth=2

# set x axis label
plt.xlabel('Number of Similar Users',fontsize=12)
# Set the y axis label
plt.ylabel('MAP',fontsize=12)
# Set a title of the current axes.
plt.title('MAP of User-based Collaborative Filtering',fontsize=18)

# show legend
plt.legend()

# show graph
plt.show()
```



4.4 MAP: Item-based Collaborative Filtering Model

In [14…

```
# map values are generated from above evaluation funciton and recorded
map_5_ib=[0.6262,0.6409,0.5795,0.58409,0.5818]
map_10_ib=[0.54204,0.62623,0.5942,0.58295,0.5647]
map_15_ib=[0.52954,0.6356,0.5998,0.5916,0.57954]
map_20_ib=[0.5375,0.6318,0.610064,0.58863,0.5795]
map_25_ib=[0.55045,0.62183,0.61166,0.59136,0.57909]
map_30_ib=[0.54242,0.62215,0.612756,0.59583,0.58371]

x_axis_ub=['1','3','5','7','10']
```

In [14…

```
# round all to 3 decimal points
map_5_ib=[round(x,3) for x in map_5_ib]
map_10_ib=[round(x,3) for x in map_10_ib]
map_15_ib=[round(x,3) for x in map_15_ib]
map_20_ib=[round(x,3) for x in map_20_ib]
map_25_ib=[round(x,3) for x in map_25_ib]
map_30_ib=[round(x,3) for x in map_30_ib]
```

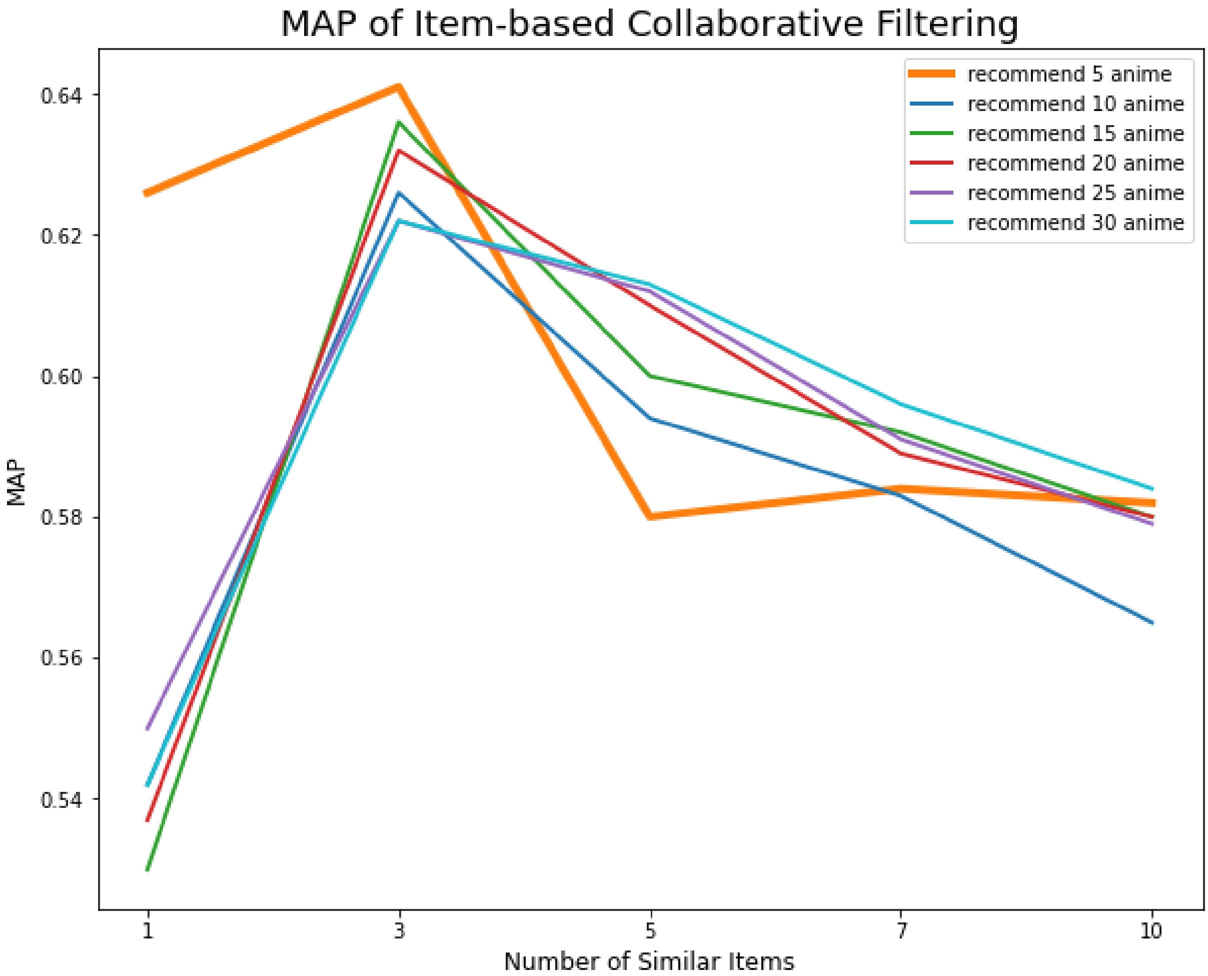
In [14…

```
# Data
df3=pd.DataFrame({'x_values': x_axis_cbv, 'y1_values': map_5_ib, 'y2_values': map_10_
                'y4_values':map_20_ib,'y5_values':map_25_ib,'y6_values':map_30_ib})
# fig sizeub
plt.figure(figsize=(10,8))
# multiple line plots
plt.plot( 'x_values', 'y1_values', data=df3, marker='', color='tab:orange', linewidth
plt.plot( 'x_values', 'y2_values', data=df3, marker='', color='tab:blue', linewidth=2
plt.plot( 'x_values', 'y3_values', data=df3, marker='', color='tab:green', linewidth=
plt.plot( 'x_values', 'y4_values', data=df3, marker='', color='tab:red', linewidth=2,
plt.plot( 'x_values', 'y5_values', data=df3, marker='', color='tab:purple', linewidth
plt.plot( 'x_values', 'y6_values', data=df3, marker='', color='tab:cyan', linewidth=2

# set x axis label
plt.xlabel('Number of Similar Items',fontsize=12)
# Set the y axis label
plt.ylabel('MAP',fontsize=12)
# Set a title of the current axes.
plt.title('MAP of Item-based Collaborative Filtering',fontsize=18)

# show legend
plt.legend()

# show graph
plt.show()
```



4.5 MAP between Models

4.5.1 Fix number of neighbors

In [14…

```
# fix number of neighbours to 5
cbv=[0.45227,0.423484,0.43559]
cbn=[0.5181,0.51136,0.51776]
ub=[0.78181,0.75833,0.74636]
it=[0.5795,0.5998,0.61166]

# round
cbv=[round(x,3) for x in cbv]
cbn=[round(x,3) for x in cbn]
ub=[round(x,3) for x in ub]
it=[round(x,3) for x in it]

# plot figure
plt.figure(figsize=(10,6))

x_axis_name = [5,15,25]

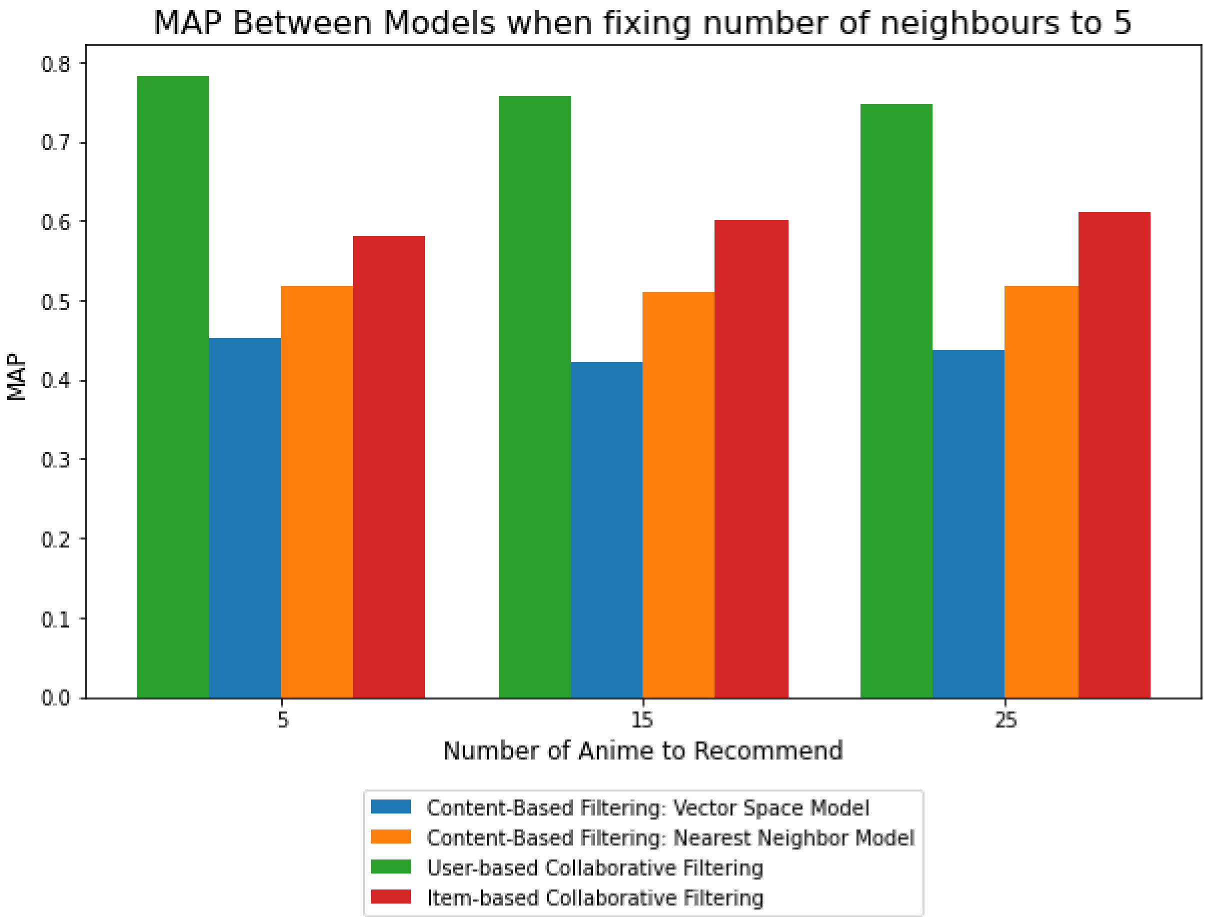
X_axis = np.arange(len(x_axis_name))

plt.bar(X_axis - 0.1, cbv, 0.2, label = 'Content-Based Filtering: Vector Space Model')
plt.bar(X_axis + 0.1, cbn, 0.2, label = 'Content-Based Filtering: Nearest Neighbor Mo
plt.bar(X_axis - 0.3, ub, 0.2, label = 'User-based Collaborative Filtering')
plt.bar(X_axis + 0.3, it, 0.2, label = 'Item-based Collaborative Filtering')

plt.xticks(X_axis, x_axis_name)
plt.xlabel("Number of Anime to Recommend",fontsize=12)
plt.ylabel("MAP",fontsize=12)
```

```
plt.title("MAP Between Models when fixing number of neighbours to 5",fontsize=16)
plt.legend(loc="lower center", bbox_to_anchor=(0.5, -0.35))

fig.subplots_adjust(bottom=0.25)
plt.show()
```



In [14…

```
# fix number of neighbours to 5: this code will show more results
cbv=[0.45227,0.4284,0.423484,0.431279,0.43559,0.4366]
cbn=[0.5181,0.509,0.51136,0.5164,0.51776,0.51935]
ub=[0.78181,0.767,0.75833,0.75113,0.74636,0.7409]
it=[0.5795,0.5942,0.5998,0.610064,0.61166,0.612756]

# round
cbv=[round(x,3) for x in cbv]
cbn=[round(x,3) for x in cbn]
ub=[round(x,3) for x in ub]
it=[round(x,3) for x in it]

# plot figure
plt.figure(figsize=(10,6))

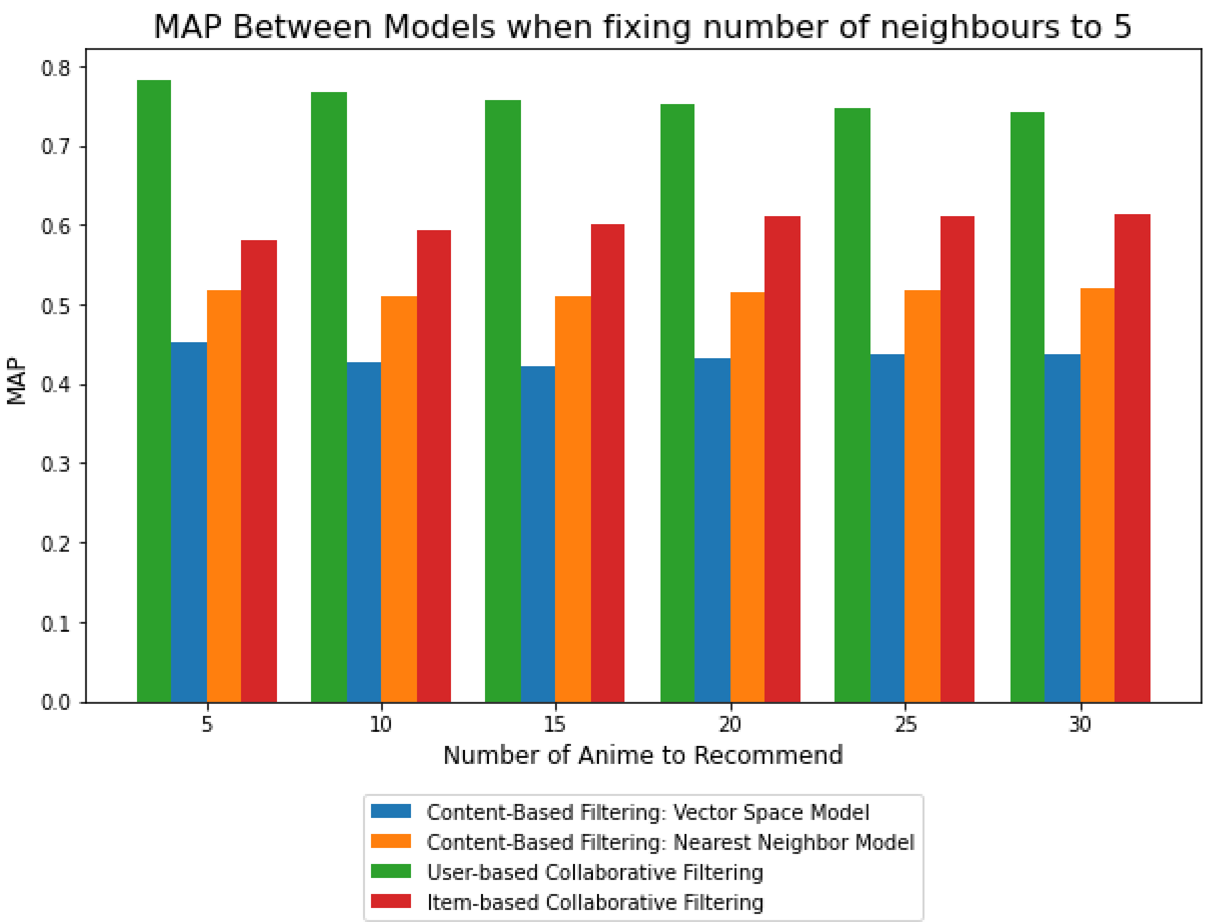
x_axis_name = [5,10,15,20,25,30]

X_axis = np.arange(len(x_axis_name))

plt.bar(X_axis - 0.1, cbv, 0.2, label = 'Content-Based Filtering: Vector Space Model'
plt.bar(X_axis + 0.1, cbn, 0.2, label = 'Content-Based Filtering: Nearest Neighbor Mo
plt.bar(X_axis - 0.3, ub, 0.2, label = 'User-based Collaborative Filtering')
plt.bar(X_axis + 0.3, it, 0.2, label = 'Item-based Collaborative Filtering')

plt.xticks(X_axis, x_axis_name)
plt.xlabel("Number of Anime to Recommend",fontsize=12)
plt.ylabel("MAP",fontsize=12)
plt.title("MAP Between Models when fixing number of neighbours to 5",fontsize=16)
plt.legend(loc="lower center", bbox_to_anchor=(0.5, -0.35))
```

```
fig.subplots_adjust(bottom=0.25)
plt.show()
```



4.5.2 Fix number of anime

In [14…

```
# fix number of anime to 5

cbv1=[0.50227,0.45227,0.42727]
cbn1=[0.57196,0.5181,0.48863]
ub1=[0.68538,0.78181,0.7999]
it1=[0.6262,0.5795,0.5818]

# round
cbv1=[round(x,3) for x in cbv1]
cbn1=[round(x,3) for x in cbn1]
ub1=[round(x,3) for x in ub1]
it1=[round(x,3) for x in it1]

# plot figure
plt.figure(figsize=(9,6))

x_axis_name = ["1","5","10"]

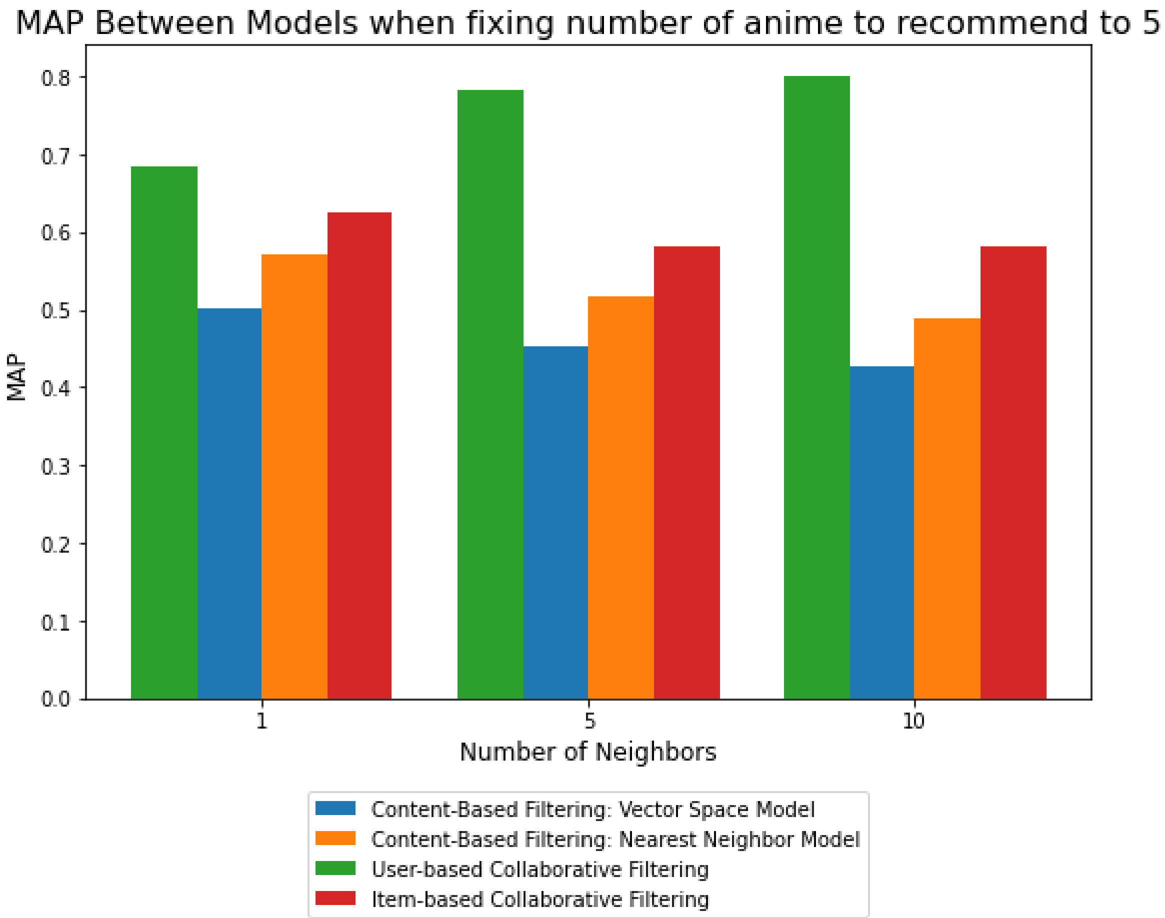
X_axis = np.arange(len(x_axis_name))

plt.bar(X_axis - 0.1, cbv1, 0.2, label = 'Content-Based Filtering: Vector Space Model
plt.bar(X_axis + 0.1, cbn1, 0.2, label = 'Content-Based Filtering: Nearest Neighbor M
plt.bar(X_axis - 0.3, ub1, 0.2, label = 'User-based Collaborative Filtering')
plt.bar(X_axis + 0.3, it1, 0.2, label = 'Item-based Collaborative Filtering')

plt.xticks(X_axis, x_axis_name)
plt.xlabel("Number of Neighbors",fontsize=12)
plt.ylabel("MAP",fontsize=12)
```

```
plt.title("MAP Between Models when fixing number of anime to recommend to 5",fontsize=
plt.legend(loc="lower center", bbox_to_anchor=(0.5, -0.35))

fig.subplots_adjust(bottom=0.25)
plt.show()
```



5. Diversity Comparison & Visualization

The way of measuring genre diversity is to measure how many out-of-box recommendations are suggested. Here, the dissertation defines genre that is not within the top 10 genre list as out-of-box genre: Any recommendations that hit out-of-box genre is defined as an out-of-box genre recommendation.

5.1 Diversity: CB vector Space

In [15…

```
# check recommendation diversity for the first user
rec_list=[]
for each_anime in relevant_anime_for_user(0):
    rec_list.append(list(get_recommendations(each_anime,5)))
```

In [15…

```
rec_list_break = []
for l in rec_list:
    for x in l:
        for element in x.split(','):
            rec_list_break.append(element)
```

In [15…

```
genders_cbv_break = []

genders_cbv = []
for name in rec_list_break[187:]:
```

```
    find_row=df_anime_final.loc[df_anime_final["Name"]==name,"Genders"]
    genders_cbv.append(list(find_row))
for l in genders_cbv:
    for x in l:
        genders_cbv_break.append(list(x.split(','))[0])

        try:
            genders_cbv_break.append(list(x.split(','))[1])
            genders_cbv_break.append(list(x.split(','))[2])
        except:
            pass

cbv_data=Counter(genders_cbv_break)
cbv_data_df=pd.DataFrame(cbv_data.items(), columns=['Genre','Frequency_cbv'])
cbv_data_df["Frequency_cbv"] = pd.to_numeric(cbv_data_df["Frequency_cbv"])
```

In [15…

```
cbv_data_df=cbv_data_df.sort_values("Frequency_cbv",ascending=False)
```

In [15…

```
cbv_data_df["outofbox"]=np.where(cbv_data_df["Genre"].isin(["Comedy","Action","Fantas
                                                             "Kids","Drama","Sci-Fi","Mus
```

In [15…

```
cbv_data_df["count_outofbox"]=cbv_data_df["Frequency_cbv"]*cbv_data_df["outofbox"]
```

In [15…

```
cbv_data_df=cbv_data_df.loc[cbv_data_df["count_outofbox"]!=0]
```

In [15…

```
# Reorder the dataframe
cbv_data_df = cbv_data_df.sort_values(by=['count_outofbox'])

# initialize the figure
plt.figure(figsize=(25,15))
ax = plt.subplot(111, polar=True)
plt.axis('off')

# Constants = parameters controling the plot layout:
upperLimit = 10
lowerLimit = 1
labelPadding = 1

# Compute max and min in the dataset
max = cbv_data_df['count_outofbox'].max()

# Let's compute heights: they are a conversion of each item value in those new coordir

slope = (max - lowerLimit) / max
heights = slope * cbv_data_df.count_outofbox + lowerLimit

# Compute the width of each bar. In total we have 2*Pi = 360°
width = 2*np.pi / len(cbv_data_df.index)

# Compute the angle each bar is centered on:
indexes = list(range(1, len(cbv_data_df.index)+1))
angles = [element * width for element in indexes]
angles

# Draw bars
bars = ax.bar(
    x=angles,
    height=heights,
    width=width,
    bottom=lowerLimit,
    linewidth=1,
    edgecolor="white",
    color="lightblue",
```

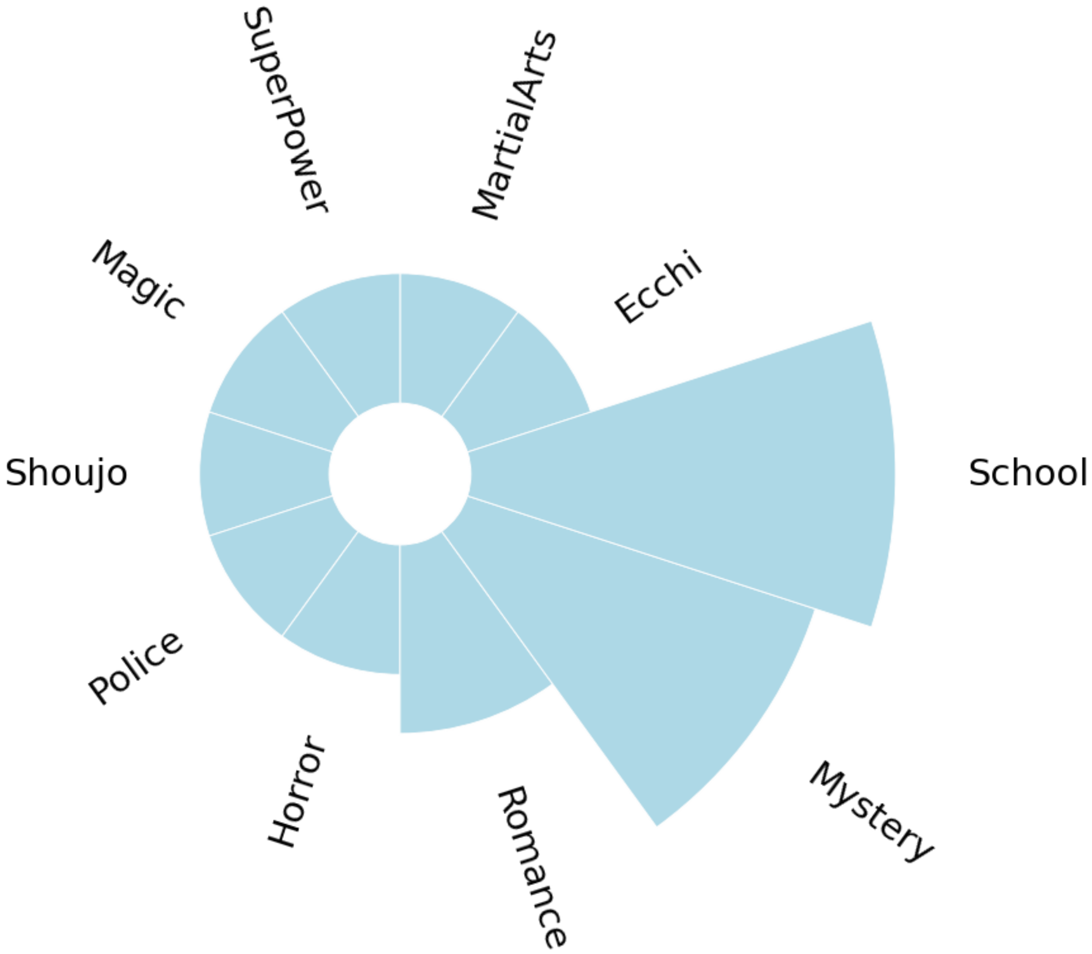
```
)

# Add labels
for bar, angle, height, label in zip(bars,angles, heights, cbv_data_df["Genre"]):

    # Labels are rotated. Rotation must be specified in degrees :(
    rotation = np.rad2deg(angle)

    # Flip some labels upside down
    alignment = ""
    if angle >= np.pi/2 and angle < 3*np.pi/2:
        alignment = "right"
        rotation = rotation + 180
    else:
        alignment = "left"

    # Finally add the labels
    ax.text(
        x=angle,
        y=lowerLimit + bar.get_height() + labelPadding,
        s=label,
        ha=alignment,
        va='center',
        rotation=rotation,
        rotation_mode="anchor",fontsize=29)
```



5.2 Diversity: CB NN Model

In [16…

```
# check recommendation diversity for the first user
rec_list_nn=[]
```

```
for each_anime in relevant_anime_for_user(0):
    rec_list_nn.append(list(print_similar_animes(each_anime)))

rec_list_break_nn = []
for l in rec_list_nn:
    for x in l:
        for element in x.split(','):
            rec_list_break_nn.append(element)
```

In [17…

```
genders_nn_break = []

genders_nn = []
for name in rec_list_break_nn[187:]:
    find_row=df_anime_final.loc[df_anime_final["Name"]==name,"Genders"]
    genders_nn.append(list(find_row))
for l in genders_nn:
    for x in l:
        genders_nn_break.append(list(x.split(','))[0])

        try:
            genders_nn_break.append(list(x.split(','))[1])
            genders_nn_break.append(list(x.split(','))[2])
        except:
            pass

nn_data=Counter(genders_nn_break)
nn_data_df=pd.DataFrame(nn_data.items(), columns=['Genre','Frequency_nn'])
nn_data_df["Frequency_nn"] = pd.to_numeric(nn_data_df["Frequency_nn"])
```

In [17…

```
nn_data_df=nn_data_df.sort_values("Frequency_nn",ascending=False)
nn_data_df["outofbox"]=np.where(nn_data_df["Genre"].isin(["Comedy","Action","Fantasy"
                                                          "Kids","Drama","Sci-Fi","Mus
nn_data_df["count_outofbox"]=nn_data_df["Frequency_nn"]*nn_data_df["outofbox"]
nn_data_df=nn_data_df.loc[nn_data_df["count_outofbox"]!=0]
```

In [17…

```
nn_data_df
```

Out[172]:

	Genre	Frequency_nn	outofbox	count_outofbox
8	Mystery	4	1	4
3	Sports	3	1	3
6	Historical	3	1	3
9	Police	2	1	2
13	School	2	1	2
15	Magic	2	1	2
7	Supernatural	1	1	1
11	Josei	1	1	1
14	Ecchi	1	1	1

In [17…

```
# Reorder the dataframe
nn_data_df = nn_data_df.sort_values(by=['count_outofbox'])

# initialize the figure
plt.figure(figsize=(25,15))
ax = plt.subplot(111, polar=True)
plt.axis('off')
```

```
# Constants = parameters controling the plot layout:
upperLimit = 10
lowerLimit = 1
labelPadding = 1

# Compute max and min in the dataset
max = nn_data_df['count_outofbox'].max()

# Let's compute heights: they are a conversion of each item value in those new coordir

slope = (max - lowerLimit) / max
heights = slope * nn_data_df.count_outofbox + lowerLimit

# Compute the width of each bar. In total we have 2*Pi = 360°
width = 2*np.pi / len(nn_data_df.index)

# Compute the angle each bar is centered on:
indexes = list(range(1, len(nn_data_df.index)+1))
angles = [element * width for element in indexes]
angles

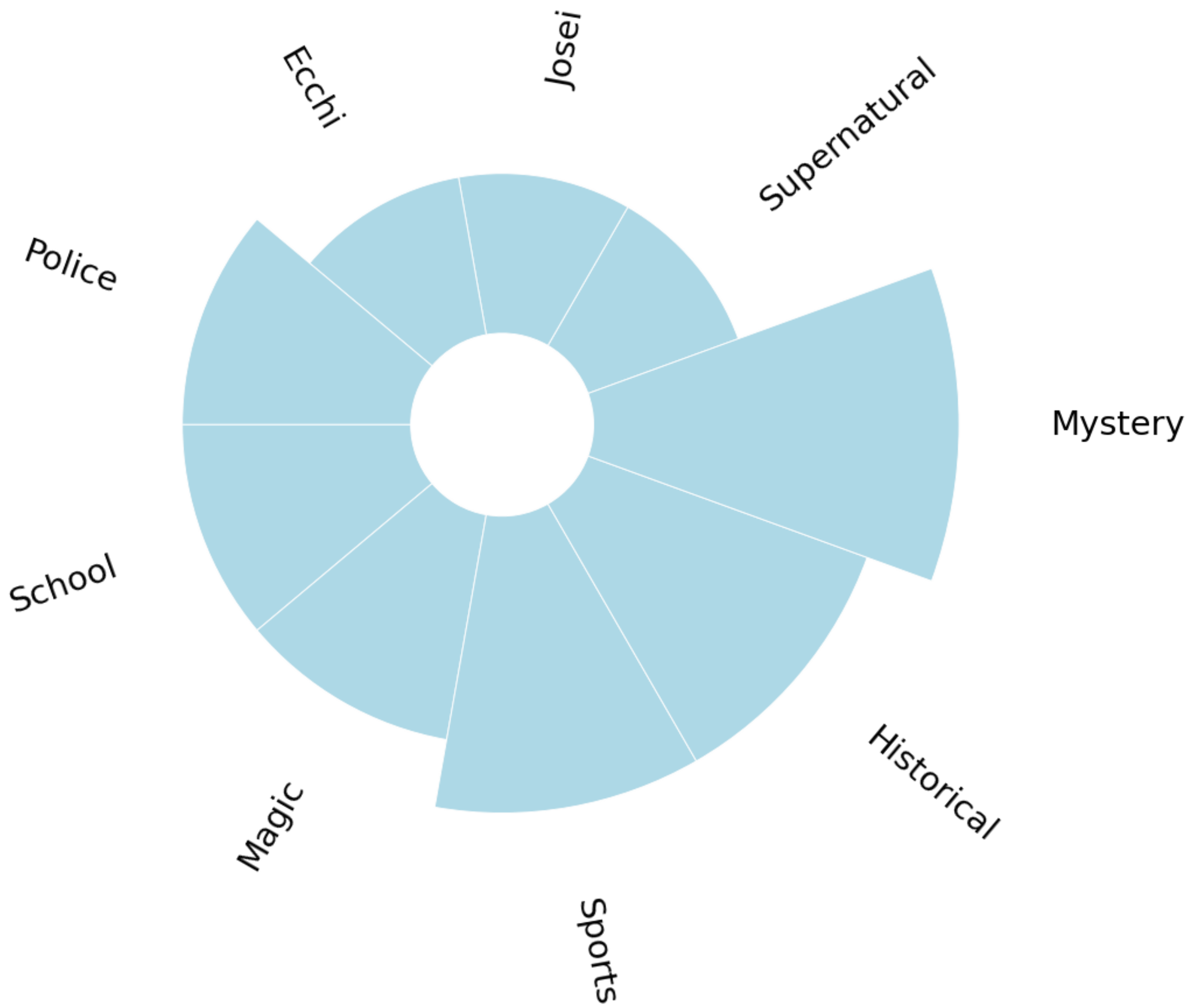
# Draw bars
bars = ax.bar(
    x=angles,
    height=heights,
    width=width,
    bottom=lowerLimit,
    linewidth=1,
    edgecolor="white",
    color="lightblue",
)

# Add labels
for bar, angle, height, label in zip(bars,angles, heights, nn_data_df["Genre"]):

    # Labels are rotated. Rotation must be specified in degrees :(
    rotation = np.rad2deg(angle)

    # Flip some labels upside down
    alignment = ""
    if angle >= np.pi/2 and angle < 3*np.pi/2:
        alignment = "right"
        rotation = rotation + 180
    else:
        alignment = "left"

    # Finally add the labels
    ax.text(
        x=angle,
        y=lowerLimit + bar.get_height() + labelPadding,
        s=label,
        ha=alignment,
        va='center',
        rotation=rotation,
        rotation_mode="anchor",fontsize=29)
```



5.3 Diversity: CF User-based

In [17…

```
# ub
genders_ub_break = []


genders_ub = []
for name in list(find_anime_cf_user(1,5,30)):
    find_row=df_anime_final.loc[df_anime_final["Name"]==name,"Genders"]
    genders_ub.append(list(find_row))

for l in genders_ub:
    for x in l:
        genders_ub_break.append(list(x.split(','))[0])

        try:
            genders_ub_break.append(list(x.split(','))[1])
            genders_ub_break.append(list(x.split(','))[2])
        except:
            pass

ub_data=Counter(genders_ub_break)
ub_data_df=pd.DataFrame(ub_data.items(), columns=['Genre','Frequency_ub'])
ub_data_df["Frequency_ub"] = pd.to_numeric(ub_data_df["Frequency_ub"])
```

In [17…

```
ub_data_df=ub_data_df.sort_values("Frequency_ub",ascending=False)
```

```
ub_data_df["outofbox"]=np.where(ub_data_df["Genre"].isin(["Comedy","Action","Fantasy"
```

In [17…

```
                                                  "Kids","Drama","Sci-Fi","Mus
```

In [17…

```
ub_data_df["count_outofbox"]=ub_data_df["Frequency_ub"]*ub_data_df["outofbox"]
```

In [17…

```
ub_data_df=ub_data_df.loc[ub_data_df["count_outofbox"]!=0]
```

In [17…

```
# Reorder the dataframe
ub_data_df = ub_data_df.sort_values(by=['count_outofbox'])

# initialize the figure
plt.figure(figsize=(25,15))
ax = plt.subplot(111, polar=True)
plt.axis('off')

# Constants = parameters controling the plot layout:
upperLimit = 10
lowerLimit = 1
labelPadding = 1

# Compute max and min in the dataset
max = ub_data_df['count_outofbox'].max()

# Let's compute heights: they are a conversion of each item value in those new coordin

slope = (max - lowerLimit) / max
heights = slope * ub_data_df.count_outofbox + lowerLimit

# Compute the width of each bar. In total we have 2*Pi = 360°
width = 2*np.pi / len(ub_data_df.index)

# Compute the angle each bar is centered on:
indexes = list(range(1, len(ub_data_df.index)+1))
angles = [element * width for element in indexes]
angles

# Draw bars
bars = ax.bar(
    x=angles,
    height=heights,
    width=width,
    bottom=lowerLimit,
    linewidth=1,
    edgecolor="white",
    color="lightblue",
)

# Add labels
for bar, angle, height, label in zip(bars,angles, heights, ub_data_df["Genre"]):

    # Labels are rotated. Rotation must be specified in degrees :(
    rotation = np.rad2deg(angle)

    # Flip some labels upside down
    alignment = ""
    if angle >= np.pi/2 and angle < 3*np.pi/2:
        alignment = "right"
        rotation = rotation + 180
    else:
        alignment = "left"

    # Finally add the labels
    ax.text(
        x=angle,
        y=lowerLimit + bar.get_height() + labelPadding,
```

```
        s=label,
        ha=alignment,
        va='center',
        rotation=rotation,
        rotation_mode="anchor",fontsize=29)
```

5.4 Diversity: CF Item-based

In [18…

```
# it
genders_it_break = []


genders_it = []
for name in list(recommend_anime_item(0,1,30)):
    find_row=df_anime_final.loc[df_anime_final["Name"]==name,"Genders"]
    genders_it.append(list(find_row))

for l in genders_it:
    for x in l:
        genders_it_break.append(list(x.split(','))[0])

        try:
            genders_it_break.append(list(x.split(','))[1])
            genders_it_break.append(list(x.split(','))[2])
        except:
            pass

it_data=Counter(genders_it_break)
```

```
it_data_df=pd.DataFrame(it_data.items(), columns=['Genre','Frequency_it'])
it_data_df["Frequency_it"] = pd.to_numeric(it_data_df["Frequency_it"])
```

In [18⋯

```
it_data_df=it_data_df.sort_values("Frequency_it",ascending=False)
it_data_df["outofbox"]=np.where(it_data_df["Genre"].isin(["Comedy","Action","Fantasy"
                                                          "Kids","Drama","Sci-Fi","Mus
it_data_df["count_outofbox"]=it_data_df["Frequency_it"]*it_data_df["outofbox"]
it_data_df=it_data_df.loc[it_data_df["count_outofbox"]!=0]
```

In [18⋯

```
# Reorder the dataframe
it_data_df = it_data_df.sort_values(by=['count_outofbox'])

# initialize the figure
plt.figure(figsize=(25,15))
ax = plt.subplot(111, polar=True)
plt.axis('off')

# Constants = parameters controling the plot layout:
upperLimit = 10
lowerLimit = 1
labelPadding = 1

# Compute max and min in the dataset
max = it_data_df['count_outofbox'].max()

# Let's compute heights: they are a conversion of each item value in those new coordin

slope = (max - lowerLimit) / max
heights = slope * it_data_df.count_outofbox + lowerLimit

# Compute the width of each bar. In total we have 2*Pi = 360°
width = 2*np.pi / len(it_data_df.index)

# Compute the angle each bar is centered on:
indexes = list(range(1, len(it_data_df.index)+1))
angles = [element * width for element in indexes]
angles

# Draw bars
bars = ax.bar(
    x=angles,
    height=heights,
    width=width,
    bottom=lowerLimit,
    linewidth=1,
    edgecolor="white",
    color="lightblue",
)

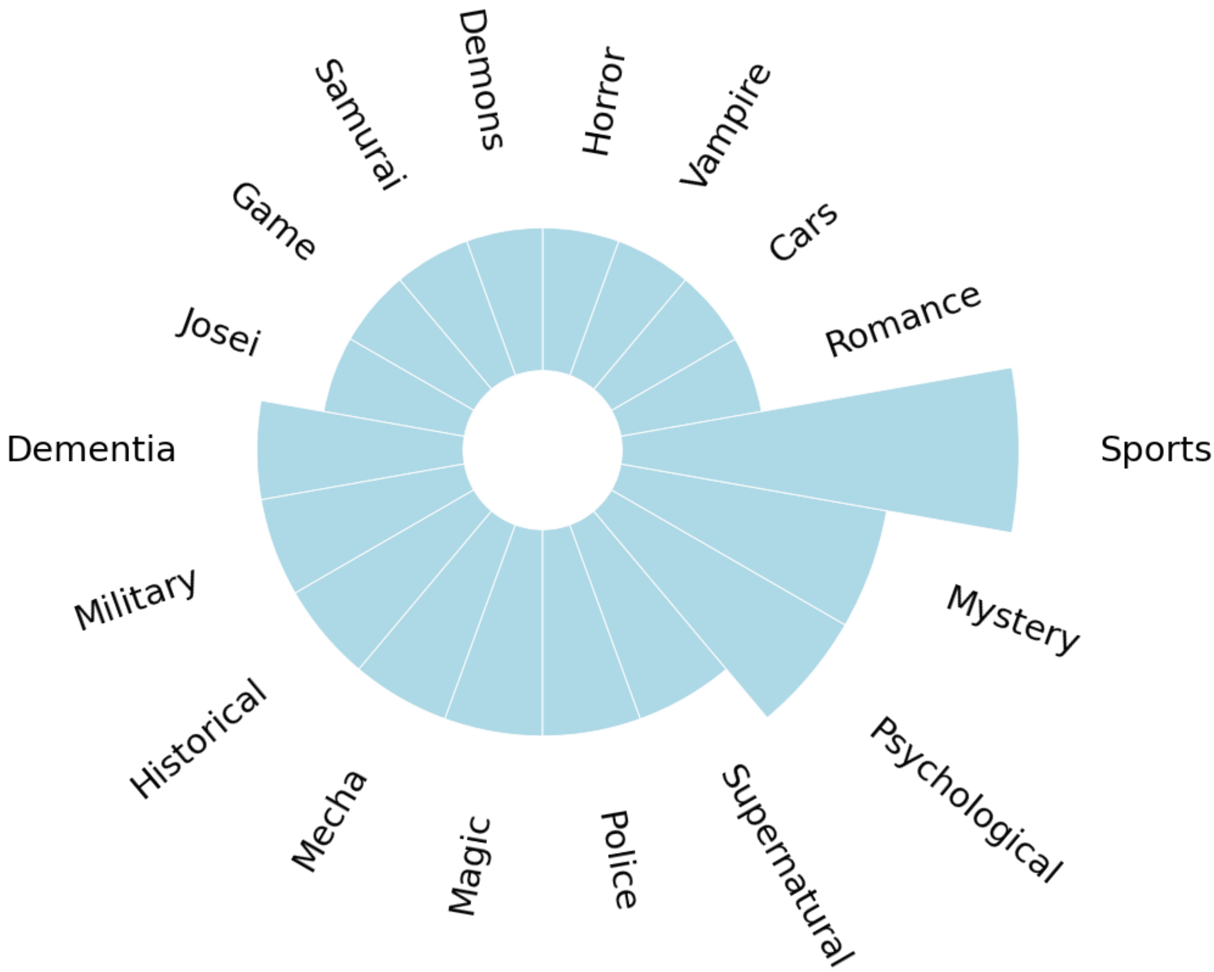
# Add labels
for bar, angle, height, label in zip(bars,angles, heights, it_data_df["Genre"]):

    # Labels are rotated. Rotation must be specified in degrees :(
    rotation = np.rad2deg(angle)

    # Flip some labels upside down
    alignment = ""
    if angle >= np.pi/2 and angle < 3*np.pi/2:
        alignment = "right"
        rotation = rotation + 180
    else:
        alignment = "left"

    # Finally add the labels
```

```
    ax.text(
        x=angle,
        y=lowerLimit + bar.get_height() + labelPadding,
        s=label,
        ha=alignment,
        va='center',
        rotation=rotation,
        rotation_mode="anchor",fontsize=29)
```



5.5 Model Comparison: out-of-box genre comparison

In [18…
```
cbv_data_df_new=cbv_data_df[["Genre","count_outofbox"]]
nn_data_df_new=nn_data_df[["Genre","count_outofbox"]]
ub_data_df_new=ub_data_df[["Genre","count_outofbox"]]
it_data_df_new=it_data_df[["Genre","count_outofbox"]]
```

In [18…
```
cbv_data_df_new=cbv_data_df_new.rename(columns={"count_outofbox":"count_cbv"})
```

In [18…
```
nn_data_df_new=nn_data_df_new.rename(columns={"count_outofbox":"count_nn"})
```

In [18…
```
ub_data_df_new=ub_data_df_new.rename(columns={"count_outofbox":"count_ub"})
```

In [18…
```
it_data_df_new=it_data_df_new.rename(columns={"count_outofbox":"count_it"})
```

In [18…
```
div_final=cbv_data_df_new.merge(nn_data_df_new, how='outer').merge(ub_data_df_new, ho
```

In [18…
```
div_final.fillna(0)
```

Out[189]:

	Genre	count_cbv	count_nn	count_ub	count_it
0	Ecchi	1.0	1.0	1.0	0.0
1	MartialArts	1.0	0.0	0.0	0.0
2	SuperPower	1.0	0.0	0.0	0.0
3	Magic	1.0	2.0	1.0	2.0
4	Shoujo	1.0	0.0	0.0	0.0
5	Police	1.0	2.0	1.0	2.0
6	Horror	1.0	0.0	1.0	1.0
7	Romance	2.0	0.0	3.0	1.0
8	Mystery	5.0	4.0	5.0	3.0
9	School	6.0	2.0	2.0	0.0
10	Supernatural	0.0	1.0	2.0	2.0
11	Josei	0.0	1.0	0.0	1.0
12	Sports	0.0	3.0	1.0	5.0
13	Historical	0.0	3.0	1.0	2.0
14	Game	0.0	0.0	1.0	1.0
15	Thriller	0.0	0.0	2.0	0.0
16	Demons	0.0	0.0	2.0	1.0
17	Psychological	0.0	0.0	4.0	3.0
18	Military	0.0	0.0	6.0	2.0
19	Cars	0.0	0.0	0.0	1.0
20	Vampire	0.0	0.0	0.0	1.0
21	Samurai	0.0	0.0	0.0	1.0
22	Dementia	0.0	0.0	0.0	2.0
23	Mecha	0.0	0.0	0.0	2.0

In [19…

```
# plot figure
plt.figure(figsize=(20,6))

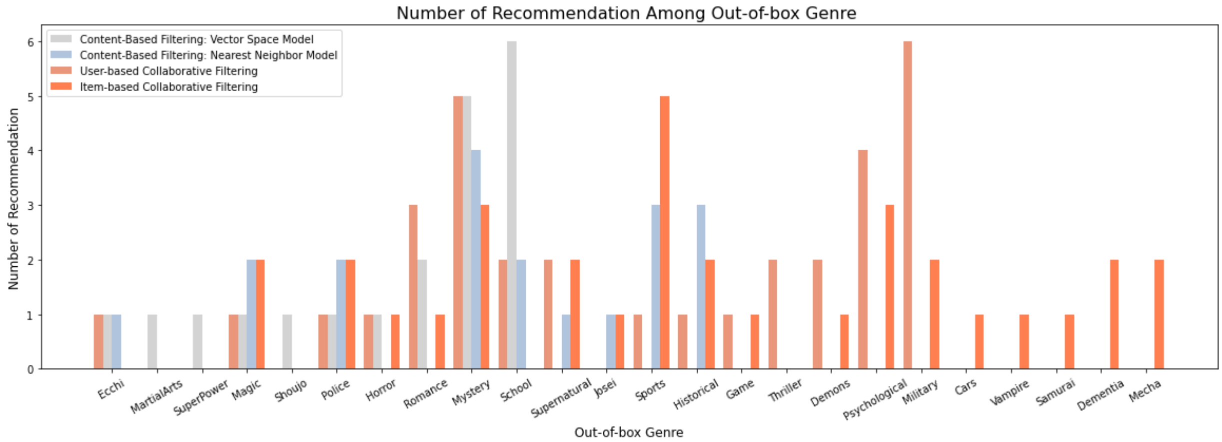
x_axis_name = list(div_final["Genre"])

X_axis = np.arange(len(x_axis_name))

plt.bar(X_axis - 0.1, div_final["count_cbv"], 0.2, label = 'Content-Based Filtering: 
plt.bar(X_axis + 0.1, div_final["count_nn"], 0.2, label = 'Content-Based Filtering: N
plt.bar(X_axis - 0.3, div_final["count_ub"], 0.2, label = 'User-based Collaborative F
plt.bar(X_axis + 0.3, div_final["count_it"], 0.2, label = 'Item-based Collaborative F

plt.xticks(X_axis, x_axis_name,rotation=30)
plt.xlabel("Out-of-box Genre",fontsize=12)
plt.ylabel("Number of Recommendation",fontsize=12)
plt.title("Number of Recommendation Among Out-of-box Genre ",fontsize=16)
plt.legend()

plt.show()
```



6. Position (Focused MAP) Comparison

In [19…

```
pos_three_all=[sum(acccuracy_three_cbv)/len(acccuracy_three_cbv),sum(acccuracy_three_r
                sum(acccuracy_three_ub)/len(acccuracy_three_ub),sum(acccuracy_three_it)/
pos_five_all=[sum(acccuracy_five_cbv)/len(acccuracy_five_cbv),sum(acccuracy_five_nn)/
                sum(acccuracy_five_ub)/len(acccuracy_five_ub),sum(acccuracy_five_it)/ler
```

In [19…

```
pos_three_all=[round(x,2) for x in pos_three_all]
pos_five_all=[round(x,2) for x in pos_five_all]
```

In [19…

```
cbv_pos=[pos_three_all[0],pos_five_all[0]]
nn_pos=[pos_three_all[1],pos_five_all[1]]
ub_pos=[pos_three_all[2],pos_five_all[2]]
it_pos=[pos_three_all[3],pos_five_all[3]]
```

In [19…

```
# plot figure
plt.figure(figsize=(9,6))

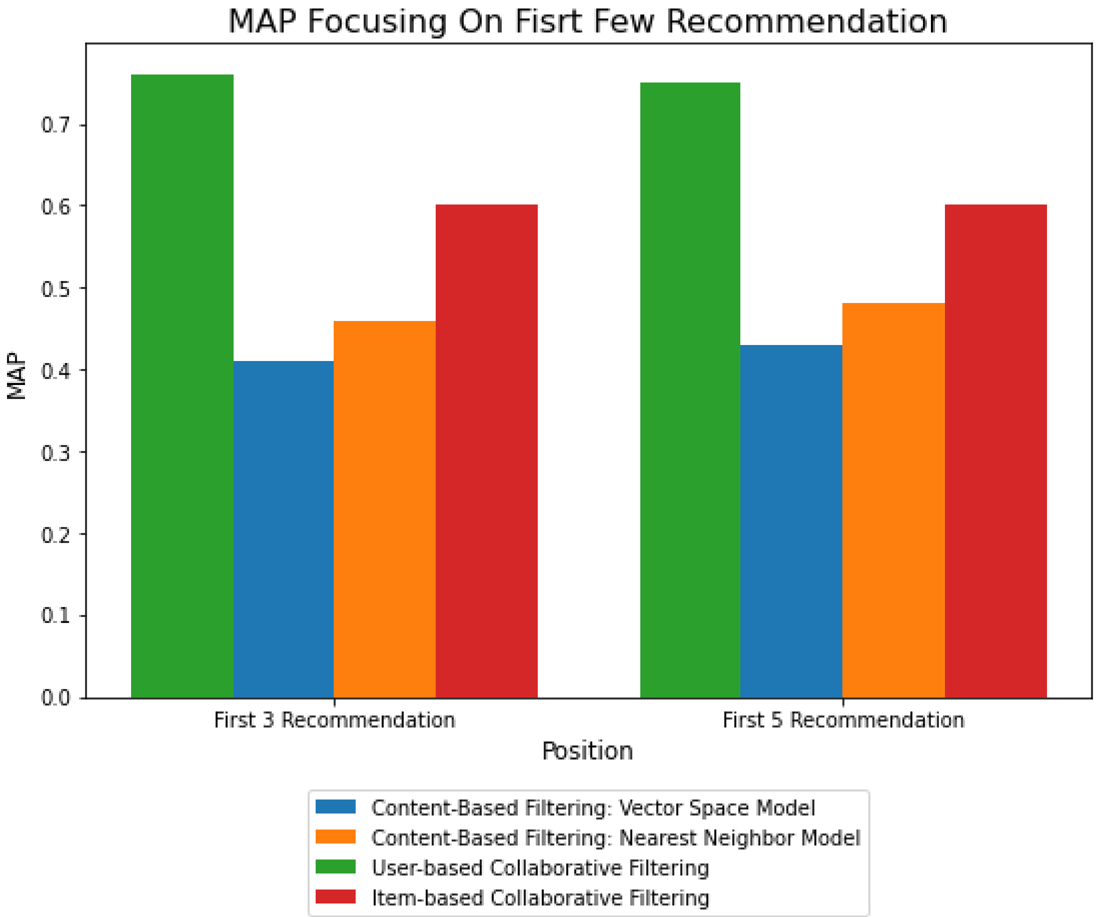
x_axis_name_pos = ["First 3 Recommendation","First 5 Recommendation"]

X_axis_pos = np.arange(len(x_axis_name_pos))

plt.bar(X_axis_pos - 0.1, cbv_pos, 0.2, label = 'Content-Based Filtering: Vector Spac
plt.bar(X_axis_pos + 0.1, nn_pos, 0.2, label = 'Content-Based Filtering: Nearest Neig
plt.bar(X_axis_pos - 0.3, ub_pos, 0.2, label = 'User-based Collaborative Filtering')
plt.bar(X_axis_pos + 0.3, it_pos, 0.2, label = 'Item-based Collaborative Filtering')

plt.xticks(X_axis_pos, x_axis_name_pos)
plt.xlabel("Position",fontsize=12)
plt.ylabel("MAP",fontsize=12)
plt.title("MAP Focusing On Fisrt Few Recommendation",fontsize=16)
plt.legend(loc="lower center", bbox_to_anchor=(0.5, -0.35))

fig.subplots_adjust(bottom=0.25)
plt.show()
```



Credits

Data extraced from Kaggle: https://www.kaggle.com/hernan4444/anime-recommendation-database-2020

References are listed in the original dissertation paper.

In [ ]: